Incorporating human behaviour in an agent based model of technology adoption in the transition to a smart grid

J. Richard Snape

Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

Institute of Energy and Sustainable Development

De Montfort University

November 2015

This PhD was partially funded by the EPSRC

Acknowledgements

Research is usually presented as a linear process, in order to ease understanding of the work undertaken and the results. In this study, as probably in most research, the process was in fact highly iterative, with many rounds of investigation, modelling, refining, re-modelling coupled with the highs and lows of results found along the way. As such, this thesis represents the culmination of around 4 years' research – interspersed with some interesting times outside the PhD, both in work and otherwise. The initial 3 years of the PhD were funded by a bursary from the Engineering and Physical Sciences Research Council (EPSRC) under grant number EP/GO59969/1.

I would like to thank a number of people for sticking with me through that journey. Firstly, my eternal thanks go to Professor Mark Rylatt who gave me the chance to do this in the first place, has been there throughout and has shown great faith in me. Sorry it took so long to finally get it finished!

Secondly to Dr. Peter Boait, who fearlessly stepped into the 2nd supervisor breach when Dr. Greig Mill left (I hope it wasn't me who scared him from the University within my first 6 months) and provided me with much inspiration alongside a critical but friendly eye. There were other supervisors and advisors along the journey – Dr. Katherine Irvine was always encouraging and saved me from the worst excesses of abusing models from psychology and Dr. Vijay Pakka, who has been a good colleague and provided me with valuable insight along the way.

Thanks also to other colleagues on the CASCADE project – Professor Peter Allen for many interesting discussions on complex systems and complexity in general, Professor Mark Savill for encouragement and sage advice on completing a PhD that I didn't always listen to enough, Drs. Mark Strathern and Liz Varga for discussions that honed our framework and Dr. Babak Madhdavi-Ardestani for helping to code for the latter two years of that project. Finally Dr. Rupert Gammon, who came to join our band rather late, but relentlessly encouraged us to look to the bigger picture.

Special thanks to Dr. Christophe Rynikiewicz for inspiring me to look a little beyond another optimising computer model! My research would likely have taken a very different path without those early discussions and the friendship that followed. Also to Professor Mark Lemon, a colleague at the Institute of Energy and Sustainable Development who has provided many, many welcome discussions over our regular coffee trips. Outside the PhD, Professor Richard Hall became a friend and we had many an interesting philosophical and political discussion encouraging me to deepen my understanding of my own position. He helped me through some hard times.

Lastly, and most importantly, thanks to my family who joined me on this faintly crazy journey. Euan, Caitlin and Aidan have provided endless moments of light relief and Fiona has shown great patience and support as I wrung my hands over countless problems which now seem so trivial. I love you all.

Abstract

The requirement for affordable, secure and sustainable energy production is a pressing global challenge and the production of electricity with low carbon emissions is crucial. This usually entails large quantities of renewable energy generation, which is intermittent and often highly distributed throughout the electricity supply system. One of the proposed schemes to manage such generation is the smart grid, the transition to which forms the context for this research.

The aim is to investigate the effect of certain psychological and social influences on the adoption of technology necessary to enable smart grids, in order to understand the implications for effective energy policy. In particular, the case of photovoltaic (PV) system adoption in the UK is studied.

Empirical data detailing PV installations registered for the Feed in Tariff is analysed in order to understand rates of adoption and how they vary across both time and space. This analysis is combined with a review of policy intervention and literature from psychology to understand drivers for adoption among householders. The results from this study are then used to inform the design of an Agent Based Model of technology adoption within the smart grid context. The decision making of householders is modelled using an algorithm based on Social Cognitive Theory. The model is used to simulate different conditions and generate adoption scenarios in order to understand the potential effects of different parameters on adoption rates.

In order to combine the analysis resulting from these methods, the multi-level perspective on transition in socio-technical systems is used to understand how a transition to a smart grid could be described and how adoption of PV in the UK under the Feed in Tariff incentive fits into such a transition.

The results show that whilst economic incentive policies have had success in some areas adoption is also dependent on many non-financial parameters. Simulations show that the observability of adoption and the perceived inconvenience or urgency of adoption can have dramatic effects on rates of adoption, in some cases outweighing the rational economic effects of financial incentives.

The implication for smart grid related policy is that non-financial factors should be taken into account as well as the more typical financial considerations in efforts to encourage adoption of necessary enabling technology by householders. The models developed could be used in further work to examine in detail adoption of other technologies such as smart home energy management systems and the interaction between adoption rates of multiple smart technologies.

Contents

1 Introduction **1**

1.1 The global context - Energy and Climate Change 2

1.2 The energy trilemma 3

1.3 Policy response – decarbonisation 4

1.4 Changes to the UK electricity supply system 5

1.4.1 Historical evolution 7

1.4.2 Future direction – toward a smart grid 8

1.4.3 Describing the system 13

1.4.4 Transition to a smart grid 14

1.5 Aims and objectives: Domestic actors' role in the transition to smart grid 15

1.5.1 Objectives 16

1.6 Thesis structure 17

2 Theoretical frame: Perspective on the transition to a smart grid **19**

2.1 Multidisciplinarity 19

2.2 Complex adaptive social system 20

2.3 Smart grid as a socio-technical system transition 22

2.3.1 Socio-technical systems 22

2.4 Transition 23

2.4.1 Interpreting socio-technical system transition 24

2.4.2 Viewing the change to smart grid as a socio-technical transition 28

2.5 Adoption and diffusion of innovation 30

2.5.1 Adopting new technology 30

2.6 Agent-based modelling 32

2.7 Overall research approach 35

2.8 Summary 36

3 Landscape: policy review **38**

3.1 Overview . . . 39
3.2 Feed-in tariff policy . . . 44
3.3 Media reporting of policy and policy changes . . . 46
3.4 Political change . . . 47
3.5 Summary . . . 48

4 Literature review **50**

4.1 Transition in energy systems . . . 50
4.1.1 General . . . 50
4.1.1.1 Computer models of transition . . . 51
4.1.2 Transition in the electricity supply system . . . 51
4.1.3 Transition to the smart grid . . . 54
4.2 Visions of the smart grid . . . 56
4.2.1 Embedded / distributed renewable generation . . . 58
4.2.2 Managing embedded renewables via demand-side management / response 59
4.2.2.1 Domestic demand response in a smart grid . . . 60
4.3 Effect of human behaviour on electricity demand . . . 61
4.3.1 Repeated behaviour vs one-off behaviour . . . 64
4.3.2 Studies of low-carbon technology adoption . . . 65
4.4 Summary . . . 67

5 Agent-based modelling (ABM) **69**

5.1 ABM in the electricity sector . . . 69
5.2 Learning and decision-making algorithms in ABM . . . 72
5.3 ABM in technology adoption and innovation diffusion . . . 75
5.3.1 ABM in adoption of low carbon electrical technology employing learning and decision making algorithms . . . 76
5.4 Summary . . . 78

6 Method: Analysis techniques and model design **80**

6.1 Parsimony, or rich description? . . . 80

6.2 FiT data analysis . . . 82
6.3 ABM method . . . 83
6.3.1 Agency – what is an agent? . . . 83
6.4 The CASCADE framework . . . 84
6.4.1 CASCADE ontology . . . 85
6.5 The adoption model . . . 87
6.5.1 The Household agent . . . 87
6.5.2 Psychological models within household agents . . . 89
6.5.2.1 Selection of Social Cognitive Theory as the pyschological model 93
6.5.3 Social modelling within agents: perception of others . . . 95
6.5.3.1 Influence of social learning . . . 97
6.6 SCT algorithm . . . 97
6.7 PV specific design . . . 99
6.7.1 Decision making algorithm . . . 99
6.7.2 Mapping the SCT to householder agent attributes . . . 99
6.7.2.1 Outcome expectations (c_{OE}) . . . 104
6.7.2.2 Perceptions of others' behaviour (c_{POE}) . . . 105
6.7.2.3 Self-efficacy . . . 105
6.7.2.4 Socio-structural factors (c_{SSF}) . . . 106
6.7.2.5 Goal (c_G) . . . 106
6.7.2.6 Behaviour (c_B) . . . 106
6.7.2.7 Outcomes . . . 107
6.7.3 Aggregator agent . . . 107
6.8 Summary . . . 107

7 Analysis of empirical data **109**
7.1 FiT registered installation data . . . 109
7.1.1 Initial data characterisation . . . 110
7.1.2 Data anomalies and treatment . . . 110
7.1.3 Effect of changes to classifications over the lifetime of FiT . . . 114
7.2 Extraction of data for PV case study . . . 114
7.2.1 Distribution of PV installed capacities . . . 115

7.2.2 Temporal distribution of PV adoption . . . 118
7.2.3 Geographical distribution of installations . . . 125
7.3 Localised Energy use data . . . 128
7.4 Demographic data . . . 131
7.5 Weather and insolation data . . . 132
7.6 Combination of datasets . . . 132
7.7 Appropriate spatial resolution . . . 139
7.7.1 Ordinal Pattern Analysis . . . 142
7.8 Summary . . . 143

8 Model parameterisations and runs 146
8.1 Experimental context design . . . 146
8.1.1 Geographical placement of houses . . . 146
8.1.2 Price of investment . . . 150
8.1.3 Policy incentives . . . 150
8.1.4 Weather . . . 150
8.1.5 The electrical grid . . . 150
8.2 Experimental design . . . 151
8.2.1 Initial configuration . . . 151
8.2.2 Model parameterisation . . . 151
8.2.3 Results Analysis method . . . 153
8.2.3.1 Spaghetti plots . . . 154
8.2.4 How many runs? . . . 155
8.2.4.1 Very large runs . . . 158
8.3 Experimental results . . . 160
8.3.1 Modelling of external shocks . . . 160
8.3.2 Effect of observation . . . 163
8.3.2.1 Observation effect parameterisation . . . 164
8.3.2.2 Effect of observation radius absolute level . . . 164
8.3.2.3 Effect of observation radius heterogeneity . . . 167
8.3.2.4 Summary of observation effect . . . 169
8.3.3 Modelled adoption rate compared to observed data . . . 171

8.4 Summary 175

9 Discussion **177**

9.1 ABM benefit for policy development 180

9.2 Changes – landscape, regime or niche? 182

9.2.1 Landscape changes - policy 184

9.3 Complexity 186

9.4 Applicability of the model 187

9.4.1 Limitations and generality 189

9.5 Summary 190

10 Conclusions and further work **193**

10.1 A transition in the complex electricity supply system? 196

10.2 Policy impacts 197

10.3 Recommendations 200

10.4 Further work 200

10.5 Summary 202

Bibliography **203**

Appendices **238**

A Published works including input from work conducted within this PhD **238**

A.1 Journal articles 238

A.2 Peer reviewed conference papers 238

A.3 Industry Journal article 239

A.4 Book sections 239

A.5 Conference paper 240

B SQL used in data analysis **241**

C Code used in data analysis **243**

List of Figures

1.1 World energy consumption, total and per capita 3
1.2 The energy trilemma 4
1.3 Schematic diagram of UK electricity grid hierarchy before addition of renewable generation e.g circa 1980 9
1.4 Schematic of hierarchical electricity grid with renewable generation circa 2010 . 10
1.5 Diagram of a smart grid configuration 12

2.1 The multi-level perspective (MLP) 24
2.2 Dynamic perspective on transition in the MLP 27

3.1 Trend in web activity for UK FiT 47

4.1 Reduction in peak load due to dynamic pricing 63

6.1 Workflow executed in this study, illustrating that the main conclusions to be drawn from an analysis of quantitative model results are qualitative in nature 81
6.2 The three interacting modules within the CASCADE framework 86
6.3 Overall view of the adoption model 88
6.4 Member variables for the Household adopter agents 90
6.5 Social learning theory 94
6.6 The SCT model 96
6.7 High level decision making algorithm program flow 100

7.1 Different geographical resolution available in the Feed-in Tariff database 116
7.2 Histogram of PV installation capacities 117
7.3 Histogram of domestic only PV installation capacities 117
7.4 Time series of PV installation at differing temporal resolution 120
7.5 Rate of PV adoption with spikes highlighted 121
7.6 Snapshots of installations per postcode district 129

7.7 Snapshots of installations per postcode district 130
7.8 UK total insolation (horizontal plane and optimal angle) 133
7.9 Scatterplot showing capacity of PV installations as a function of IMD score for each LLSOA 134
7.10 Region of interest from Figure 7.9 135
7.11 Capacity of installed domestic PV against the fraction of housholds that are owner occupied per LLSOA 136
7.12 Scatterplots of electricity use in LLSOA against installed domestic PV capacity . . 137
7.13 Installed domestic PV capacity as a function of Households per Hectare in each LLSOA 138
7.14 Logarithm of installed domestic PV capacity as a function of household density . 138
7.15 Snapshots of capacity installed divided by household density per LLSOA 140
7.16 Deficiency of least squares measure of fit for adoption timeseries 141

8.1 Illustration of position of LE2 postcode sector within the UK 148
8.2 Diagram of LE2 area 149
8.3 Domestic building layout in LE2 area 149
8.4 Buildings showing a sample of DEFRA pro-environmental category assignment . 153
8.5 10 runs of simulation model with % adoption 155
8.6 Histogram of end states after 10 runs (% adoption) 156
8.7 50 runs of simulation model with % adoption 156
8.8 Histogram of end states after 50 runs 157
8.9 200 simulation runs outcome of % adoption 157
8.10 Histogram of end states after 200 runs (% adoption) 158
8.11 End of pathway distributions for 5000 runs of simulation with high financial incentivisation and μ=25 and $\sigma^2 \in \{0, 10\}$ 159
8.12 Simulated and empirical adoption rates to end of 2011 in LE2 area 162
8.13 Histogram of initial adoption state (x axis is % of agents with PV at initalisation) . 163
8.14 Adoption with all agents observing a 20 unit radius 165
8.15 Adoption fraction with all agents having observation radius 22.5 units 166
8.16 Adoption fraction with all agents having observation radius 25 units 167
8.17 Adoption percentage with homogeneous radius 168

8.18 Adoption percentage with heterogeneous observation 168
8.19 Spaghetti plot for $r \sim N(10, 7.5)$ 172
8.20 Histogram of end states for $r \sim N(10, 7.5)$ 172
8.21 Illustrative pathway from a particular output (seed 45 from ensemble $r \sim N(10, 7.5)$) 173
8.22 Observed adoptions per week in LE2 postcode district 174
8.23 Cumulative count of adoptions in LE2 postcode district. 174
8.24 Observed data overlayed on model run spaghetti plot 175

9.1 Cumulative number of adoptions under the FiT to 2015 179

List of Tables

1.1 Comparison of the characteristics of conventional and smart grids 13

2.1 ABM characteristics and relevance to this study 33

3.1 Key UK policies and strategy documents affecting smart grid transition, with focus on PV adoption 40

5.1 Classification of learning algorithms employed in Agent-based modelling. 73

6.1 Comparison of behaviour change theories 92

6.2 Mapping SCT constructs to model variables 101

7.1 Description of FiT database (See Appendix section B.1 for SQL) 111

7.2 Available fields in FiT database (See Appendix section B.2 for SQL) 111

7.3 Basic description of photovoltaic installations registered for FiTs 115

7.4 Descriptive statistics of domestic PV installation capacity 118

7.5 Data on the PV adoption rate peaks 121

7.6 Correspondence between policy change, announcement date and PV adoption rate peaks 123

7.7 Photovoltaic installations by type and availability of postcode geographical information 126

7.8 Photovoltaic installations by type and availability of LLSOA geographical information (Scotland excluded) 127

7.9 Model parameters derived from the empirical data analysis 144

8.1 Mapping pro-environmental category to numerical representation of ability and propensity to install 151

8.2 Construct values 161

8.3 Relationship weights 161

8.4 Neighbourhood vicarious learning model parameters 164
8.5 Summary of pathway outcome distributions for all vicarious learning parameter combinations 169

Chapter 1

Introduction

This thesis describes research into the representation and effect of human learning and behaviour in an Agent-Based Model (ABM) of low-carbon technology adoption. The focus is on domestic actors in the UK and the context is the potential transition to a smart grid. Smart Grid as a concept describes an electricity network that can intelligently balance supply and demand in order to efficiently deliver sustainable low carbon, economic and secure electricity supplies. Accordingly, a smart grid will offer all users of the network access to real time data describing their usage and, potentially, information about the electricity market that was previously the preserve of large corporate players. In turn, to benefit from a smart grid, users will need to process and respond to that information to some degree, either manually or using smart technology. The nature of this response is far from trivial and will depend on the behaviour of both consumers and their installed technology as the electricity market is brought into the home and workplace. In turn, that behaviour is subject to complex phenomena such as attitude, habit, social influence and learning. A radical change is envisaged, to a system where all users employ a dynamic consumption strategy either directly or through an intelligent automated device often coupled with local microgeneration. To understand this change, a powerful modelling approach which can describe the behaviour and learning of actors and resulting emergent system behaviour is necessary.

The research was carried out as part of the CASCADE project, which had wider aims to develop an ABM framework to enable modelling of various aspects of a potential UK smart grid. CASCADE models the smart grid as a system comprising the physical layer (infrastructure), along with individual, collective (corporate, regulatory, community) and automated (software) agents and their associated networks (economic, information transmission and social). The PhD research described contributed toward the project as significant amounts of the framework were designed and implemented by the author.

However, the model described in this thesis and implemented within the framework was the sole work of the author. Where generic framework features are described, these are clearly attributed to previously published work and where the author's work has been contributed to the framework this is similarly highlighted in the text. The framework is open source and available for inspection at any time (www.github.com/rsnape/cascade); all contributed code is tagged with its authors' unique identifier.

Publications containing substantial contributions based on the work undertaken in this thesis are presented in Appendix A. The remainder of this introduction describes the context in which the study is undertaken and the motivation for the research in more detail, concluding with the specific aim of the research described and an outline of the thesis structure.

1.1 The global context - Energy and Climate Change

Energy for heating is a basic human need and in most countries the provision of energy has become a requirement of government. In many countries, the right to consume energy is now assumed for many purposes beyond basic survival needs, whether at home or work. Long distance travel, cooking, refrigeration, lighting, watching TV and myriad other energy intensive activities are now an integral part of many people's life. Energy is predominantly consumed by end users as electricity, natural gas for space heating and cooking, or oil as transport fuel.

Increasing population coupled with increases in global wealth and energy using devices have led to growth in the amount of energy used on the planet at an increasing rate (Fouquet and Pearson, 2012). The growth in demand has been particularly pronounced since circa 1940. Per capita consumption remained approximately constant between 1990 and 2000, but appears to be rapidly increasing once again. Throughout the 20th century, energy for electricity, heat and transport was provided largely by fossil fuels and, despite the increase in nuclear and renewable sources in recent decades, around 90% of energy needs are still met from fossil fuels as the primary fuel (Figure 1.1).

Unfortunately, the use of fossil fuels to satisfy the growth in energy demand has entailed the emission of Carbon Dioxide (CO_2). The emission of CO_2, and more generally the Greenhouse Gases, contribute to changing the Earth's climate. It is now widely accepted that the present levels of anthropogenic CO_2 emission will contribute to climate change. The International Panel

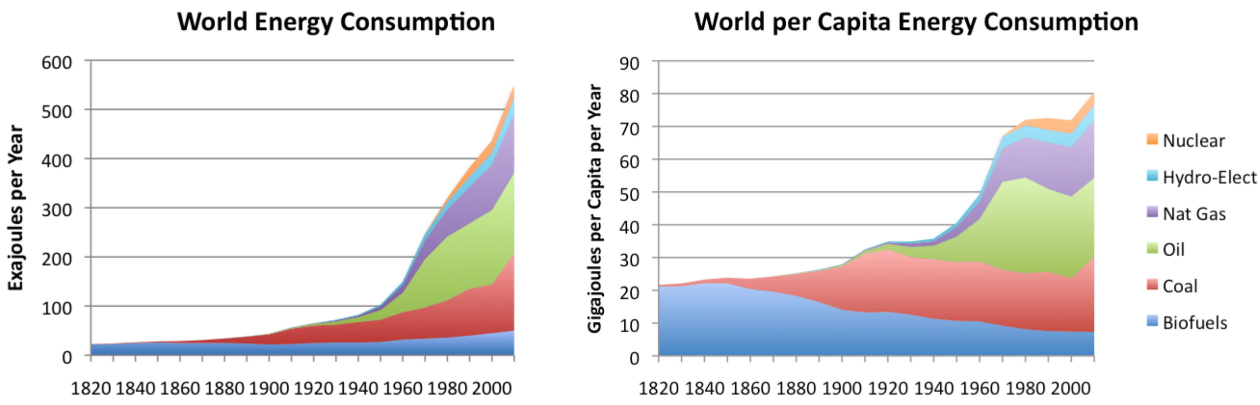


Figure 1.1: World energy consumption, total and per capita

Source: (Oil Drum, 2012)

on Climate Change (IPCC) conducts a regular wide ranging review of the scientific literature, the most recent of which found that "*warming of the climate system is unequivocal*" and that:

"Human influence on the climate system is clear. This is evident from the increasing greenhouse gas concentrations in the atmosphere, positive radiative forcing, observed warming, and understanding of the climate system."

Source: (IPCC, 2013)

The exact sensitivity and response of the climate to anthropogenic emissions is still under investigation and estimates of expected warming and the uncertainty in these predictions remain an open area of research (Skeie et al., 2014). In turn, the consequences of climate change are contested, but it is widely thought that climate change may have a deleterious effects on large segments of the Earth's population (IPCC, 2014). The need to mitigate climate change is seen as one of the largest challenges facing humanity today.

1.2 The energy trilemma

The use of the term trilemma has become common to describe the competing pressures on governments to meet climate change obligations in combination with the long-standing need to maintain energy security and keep retail prices as low as possible in the face of rising wholesale energy prices (e.g. Boston, 2013; Foxon, 2013).

A strategy must be devised to ensure that future sustainable energy systems deliver energy

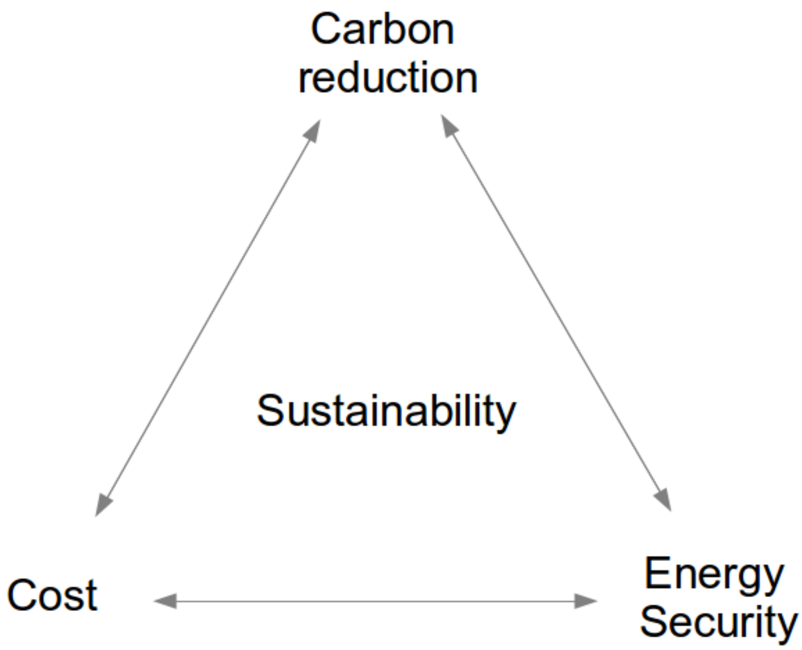


Figure 1.2: The energy trilemma illustrating the objectives that a sustainable energy system must meet.

Source: after (Boston, 2013)

that satisfies a balance of the following requirements.

1. **Secure –** energy is available when needed
2. **Economic –** energy is provided at the affordable cost
3. **Environmental –** energy supply must reduce CO_2 emissions

This is usually presented as a triangle of competing objectives, with sustainable solutions sitting as close to the centre as possible (Figure 1.2). Investigation of how the UK could move toward a sustainable energy system balancing the needs of the trilemma forms the primary motivation for this study.

1.3 Policy response – decarbonisation

The conclusions of the IPCC and the problems associated with climate change have been recognised and broadly accepted by governments worldwide. There are two main options to respond to climate change:

1. **Mitigation** – make changes to avert climate change by reducing GHG, mainly CO_2

2. **Adaptation** – accept the changes in climate due to anthropogenic emissions and put in place policies to adapt to its consequences.

Focus is usually on mitigation to avert the worst potential climate changes, although there are calls from economists to consider whether adaptation would be a more cost effective way to respond. Policies to address climate change have permeated all levels of governance, from the global UN Kyoto protocol, through continent-wide measures (e.g. EU directives) to national, sub-national and corporate strategies, policies and plans. This landscape of policy measures is detailed in Chapter 3.

In the UK, the government has made legally binding commitments to reduce CO_2 emissions to 80% of 1990 levels by 2050 (UK Parliament, 2008a). The magnitude of change needed in energy systems in order to achieve these aims has been articulated by the Chief Scientific Adviser to DECC (MacKay, 2008). From large corporations and central government to local councils and individuals, people are making efforts to introduce wide ranging changes to reduce CO_2 emissions, in an endeavour to meet these targets and avoid or limit potential negative consequences of climate change. Measures taken include interventions intended to promote the use of technologies that are designed to reduce emissions as well as to change the behaviour of individuals, communities or corporations. Such interventions range from advice, through practical assistance and incentivisation to regulation and law making.

1.4 Changes to the UK electricity supply system

This study focuses on the UK electricity network. In the UK, electricity generation is a major contributor to CO_2 emissions, contributing 27% of total UK emissions in 2009 (DECC, 2010a). In order to meet CO_2 reduction targets the UK government strategies place a heavy emphasis on moving toward the use of electricity as the primary energy source for transportation and heating (Ofgem, 2008). This plan is based on moving from carbon intensive heating (via natural gas) and transportation (conventional fuels) to electricity because it is more feasible to decarbonise. The strategy therefore relies on the electricity being generated using low carbon sources.

Low carbon generation includes nuclear power stations and renewable generators, such as wind turbines, solar photovoltaic panels, hydroelectric generators and others. Some low carbon generation is already connected to the grid, but almost all strategies for decarbonisation of electricity supply envision a far greater number of renewable electricity generators on the grid, whether such generators are at large scale or small.

The increase in renewable generation presents issues for the electricity supply system:

1. **Decreased predictability -** Large scale generation will no longer be highly predictable or available for dispatch at any time, for instance large wind farms provide electricity when the wind blows, which does not necessarily coincide with when it is needed. Such intermittency is present in renewable generation at all scales.

2. **Decreased central control -** The ability to switch individual generators on or off to meet demand and stability criteria will be lessened in a grid with many small generators distributed around the network.

3. **Change in function** of lower voltage (distribution) network - smaller and medium scale generators are connected to the local lower voltage cables (known as the distribution network) rather than the very high voltage transmission network as currently. As more and more consumers install small renewable generators, power flows will become bidirectional where they have traditionally been unidirectional – as (at some points in time at least) more electricity is generated than consumed by certain buildings.

The move to electrical heating and transportation similarly poses challenges:

1. **Overall demand increase –** This is projected to increase to levels 2.5 to 3 times greater than today (Winser, 2010) Dealing with this using business as usual methods (installing more cables) could cost up to £36 billion (Pudjianto et al., 2013).

2. **Change in demand pattern –** heating and car charging loads are likely to change the well known patterns of demand as they consume electricity at different times of day (for instance overnight).

The strategy of utilising electricity generation which is both less predictable and distributed throughout the network implies a change in the way that the grid is used and managed if security of supply is to be maintained. An increase in overall demand and potential changes to demand patterns and peak imply that the electricity grid must increase its capacity or utilise existing capacity more efficiently. Thus, in order to meet the targets for decarbonisation without getting caught on the security and cost horns of the trilemma, a new way to manage energy generation and consumption is required. One concept proposed to perform such management is the Smart Grid; this research aims to investigate how human behaviour may affect the transition to a smart grid.

In order to understand these issues and the potential smart grid solution that this research explores, a brief history and description of the network and changes envisaged is given in the following sections.

1.4.1 Historical evolution

The electricity network rapidly grew from a number of disjoint areas with local electricity provision in the 1930s to the National Grid of today, with almost all households in the UK connected to a nationwide network which supplies electricity on demand. Between 1933 and 1990, the network evolved under centralised conditions, where large power stations were owned and operated by the state via the Central Electricity Generating Board (CEGB) and generated electricity sufficient for many millions of homes connected to the grid. Power flowed from generators through a complicated network to be consumed at the far reaches of the network. Although the central authority was broken up in 1990 and economic competition was introduced, the physically centralised and hierarchical design of the grid remains and a central System Operator (National Grid plc) is still responsible for the dispatch of generators in order to maintain grid supply equal to demand (balance) and therefore voltage and frequency stability. The flow of power is essentially unidirectional (from large generator through numerous transformers to end use) and the existing grid is designed and constructed to optimise the flow from large generators at very high voltage (through the transmission grid) via various lower voltage levels (the distribution grid) to the low voltage domestic supply (Figure 1.3). The quantity and timing of generation is led by demand.

Since 1990, the amount of renewable generation on the grid has increased. Typically, renewable generators (including rather large wind farms) are connected to the distribution grid (lower voltage e.g. $<= 33$kV) rather than the transmission network (Figure 1.4). Generators connected in this way are termed embedded generators. Larger installations are given dedicated connections rated by the Distribution Network Operators (DNOs) to cope with the new load on the grid, whilst domestic and small commercial installations usually connect to the existing grid infrastructure.

Until very recently the embedded generators presented little challenge to the DNOs as, even in optimal weather conditions, the electricity they generated was far exceeded by the demand on any particular cable. Similarly, there has been very little use of electric vehicles or heat pumps affecting demand. Thus, the assumptions of well known, reasonably predictable demand and uni-directional flow have remained valid. With the advent of policies to promote large scale adoption, as well as those proposing vastly increased demand via electrical heating and transport, this assumption is likely to change. It is this change that the research described investigates.

1.4.2 Future direction – toward a smart grid

The fundamental vision motivating interest in smart grids is that enhanced real-time information can be used to influence demand to match supply in addition to the present operating method where supply is adjusted to meet demand. Such matching of demand to supply is new and may be done at many scales, from within a building, to a community to a wide geographic area. In the UK, it is proposed that using a smart grid to deal with increased loads might save up to £25bn compared to the £36bn "business as usual" cost of simply reinforcing the grid to cope with the much higher demands and peak supplies created by intermittent renewable generators (Pudjianto et al., 2013). Smart Grid is a relatively new concept and there are a number of definitions of both the term and pathways to its implementation. This research was based upon the definition of the European Technology Platform, which describes smart grids as:

'Electricity networks that can intelligently integrate the behaviour and actions of all users connected to it - generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies."

Source: *(ETP, 2006)*

It is crucial to note that by this definition, the participatory behaviour of all consumers and generators is considered a part of a smart grid, as well as the technical infrastructure itself. The vision is that some erstwhile consumers will become both consumers and producers of electricity and these are often termed prosumers (after Toffler, 1981). This implies a requirement that all users of the network provide near real time information about consumption and generation, as well as processing and responding to near real time information sent to them by grid operators

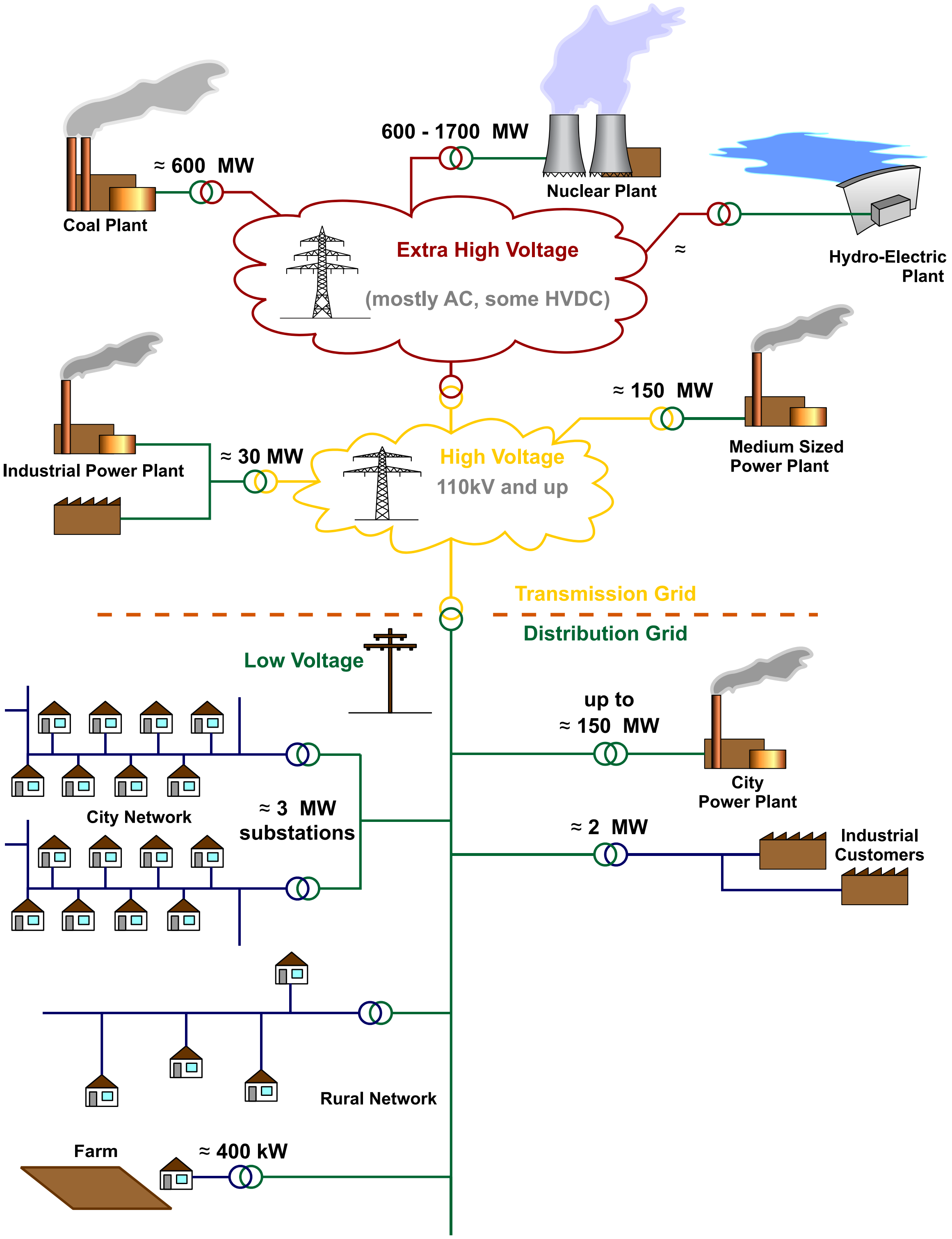


Figure 1.3: Schematic diagram of UK electricity grid hierarchy before addition of renewable generation (e.g circa 1980). 33kV and lower voltage cables are termed the distribution grid (dark green) whilst higher voltage (132kV+) are termed the transmission grid (yellow).

Source: (MBizon, 2010), CC-BY license, with alterations by Snape

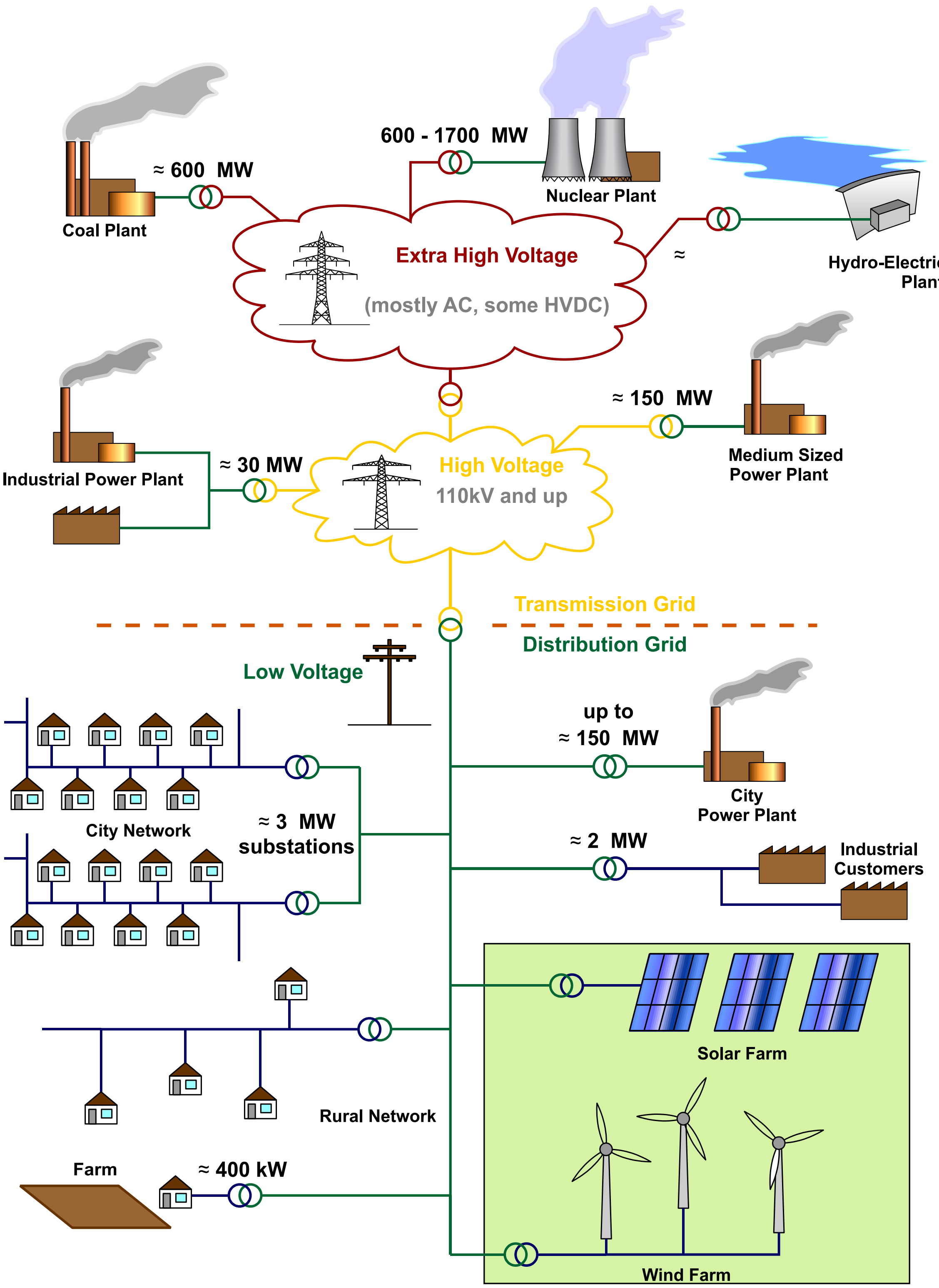


Figure 1.4: Schematic of hierarchical electricity grid with renewable generation circa 2010. Note the recent addition of wind and solar farms at the 110 or 32 kV levels (green highlighted background) as compared to Figure 1.3.

Source: (MBizon, 2010), CC-BY license, with alterations by Snape or suppliers. This new role and its implication for methods used when modelling the grid are discussed in more detail in the model design section (6.5). The main implication is that models characterising end users as pure, predictable loads are inadequate; load will be influenced by human behaviour with regard to both device ownership and operation to a greater degree than today. This is an important part of the approach taken in this research – technical and social elements of the Smart Grid concept are studied in tandem.

An illustration of how this vision might change the grid from the one way flows implicit in Figure 1.4 is shown in Figure 1.5. All the essential differences considered are present, with large scale renewable generation, small distributed renewable generation (also referred to as micro-generation), electric vehicles and heating and potential two way energy flows. In addition, communications networks are present to provide real-time or near-real time information both from consumers to suppliers and vice-versa. The contrasts between existing infrastructure and future smart grid are summarised in Table 1.1.

Figure 1.5: Diagram of smart grid configuration

Source: http://abetterenergyplan.ca/images/cms/smart-what-is-smart-grid.jpg

1.4.3 Describing the system

In order to assist in describing the system under consideration, the term *electricity supply system* will be used. It is used to describe the entire means by which electricity is provided to its point of use, encompassing technical (e.g. generators, machines at point of use, the National Grid), economic (e.g. wholesale markets, retail contracts), socio-demographic (e.g who uses what, why and where) and political & regulatory elements.

It is usual to include end users within the system boundary in energy systems models: the Global Energy Assessment states:

"The energy system comprises all components related to the production, conversion, and use of energy."

Source: (Grubler et al., 2012)

Such definitions of system may be criticised as they are generally open systems, however the working term electricity supply system is consistent with definitions of energy systems within the literature (Pfenninger et al., 2014).

Table 1.1: Comparison of the characteristics of conventional and smart grids

Source: Rylatt et al. (2015, Table 1)

Existing infrastructure	**Smart grid**
Central generation	Distributed and central generation
Mainly dispatchable generation	Large proportion of poorly dispatchable generation
Passive consumers	Active consumption, with quantity consumed changing in response to context, including a mix of automatic and manual control which requires behaviour change
Basic meters providing total consumption with readings taken at billing intervals (typically three monthly)	Smart meters providing near real time consumption information

Existing infrastructure	**Smart grid**
Little dispatchability of demand	Dispatchable demand (Demand Side Response / Active Demand): distributed control
Largely passive physical networks	Active networks (with communication), for example automatic tap-changing on transformers to stabilise voltage
Hierarchical uni-directional power flow from central generator to distributed consumers	Bi-directional power and data flows
High redundancy (extra cost)	Intelligent use of assets (cost savings) deployment of minimum assets based on sophisticated analysis of failure risk. Self re-configuring / healing networks.
Vertically integrated Utility companies	Multiple supply business models including ESCos, MuSCos, etc.

1.4.4 Transition to a smart grid

The broad UK pathway to achieve a smart grid is set out in the Energy Networks Strategy Group routemap (ENSG, 2010). This document describes roll-out of smart metering infrastructure between 2010 and 2020 and *"well targeted [smart grid] pilot projects between 2010 and 2015"*, with widespread penetration of electrified transport, electrified heating and distributed generation from 2020 onwards. Unfortunately detail is limited. Although widespread penetration of technology dealing with relatively large quanta of electricity is envisaged, there is considerable uncertainty as to the final configuration of the smart grid, its effects on grid usage and the transition from today's grid to that configuration. Understanding the scenarios, or pathways, of transition to a smart grid under different incentives, regulations and policies is of paramount importance.

In addition to the final changes in both behaviour and technology, the phasing or order in which transitions occur will have a great impact on the system and its evolution. For instance, if large scale electric vehicle adoption is incentivised and occurs before significant smart control infrastructure is deployed, the peak loads as everyone charges their vehicles could impose great stress on the electricity grid and lead either to failure, or costly reinforcement.

The drivers of changes in behaviour and technology adoption may be government policy, often in combination with economic motivation. However, for such changes to materialise, they must be adopted by citizens. Individual decisions to change are the result of behaviour influenced by markets, advertising, significant political lobbies and individual consumer perceptions, beliefs and norms. Given the manifold interventions being made to complex systems of energy consumption, it would be extremely valuable to be able to model their effects. Such a model could incorporate different assumptions regarding the above factors when designing policy and regulation, in a structured simulation framework. The model could aid the description and evaluation of scenarios with and without given interventions and would assist in selection of appropriate interventions and implementation strategies.

A powerful modelling approach which can describe the behaviour and learning of actors and resulting emergent system behaviour is necessary. A promising technique to model such complex adaptive systems and interventions affecting them is ABM, which is particularly suitable when modelling scenarios where interaction between actors is important and those actors display heterogeneity in variables of interest. ABM is used in this study and is described in more detail in Section 2.6 and Chapter 5.

1.5 Aims and objectives: Domestic actors' role in the transition to smart grid

This thesis argues that representing human learning and behaviour in a model describing the transition toward a smart grid can greatly aid understanding of such a transition and therefore policy making designed to effect it. Section 1.4.4 describes the way in which such a transition will require widespread penetration of new technology and energy consumption practice. That penetration requires users of the network to adopt these technologies and practices. This research concentrates on that adoption, specifically in a domestic context. The aim of the investigation is to answer the following question:

"What effect does the behaviour and learning of domestic consumers with respect to technology adoption have on potential transition to a smart grid?"

In order to consider this question from an empirical as well as theoretical point of view, it was necessary to select a particular technology, integral to proposed smart grids, for which adoption could be considered in depth. The technology selected was photovoltaic (PV) systems. The reasons for this were fourfold:

1. Distributed renewable electricity generation technology is a group of technologies that forms an integral part of smart grid visions.

2. Adoption of PV in a domestic context is the most well advanced technology adoption in the smart grid context.

3. Explicit policy has been adopted in the UK to encourage PV adoption (among other renewable technologies) – the UK Feed-in Tariff (FiT) (UK Parliament, 2008b) and subsequent alterations to it (UK Parliament, 2011). This allows for analysis of the effect of policy on adoption.

4. Data on the temporal and spatial distribution of adoption is openly available.

1.5.1 Objectives

To structure the research, the overall aim was broken down into eight subsidiary objectives:

1. Determine an appropriate theoretical perspective from which to study potential transition to a smart grid. Whilst the overall context for the study is the transition to a smart grid and the research does not seek to critique the concept or desirability of the smart grid in itself, it is necessary to define a theoretical position from which a transition (or potential transition) may be analysed.

2. Determine the most important behaviours at a domestic level in terms of affecting transition to a smart grid.

3. Investigate the strengths and limitations of ABM as a technique to model the smart grid transition in the context of other possible methods, including considerations of scale in time and space alongside the potential to model human behaviours.

4. Select an appropriate behavioural model as the basis for agent behaviour in the ABM

5. Utilise existing secondary data sources to understand spatial and temporal characteristics of adoption in the target system and determine appropriate model scale.

6. Implement an ABM with the capability to model observed pattern of domestic photovoltaic (PV) adoption in the UK.

7. Model influence of important psychological and sociological characteristics on PV adoption behaviour.

8. Analyse PV model results combined with policy and real world data to understand potential effects of policy on transition to a smart grid.

The PV case study demonstrates the benefits of socio-technical simulation in understanding potential transitions to a smart grid, the advantages of the approach taken and the complexity of the system dynamics influencing the transition. The effect of rate and phasing of adoption with respect to smart behaviour of the grid is then discussed.

1.6 Thesis structure

The thesis is structured as follows, addressing the objectives described above. Chapter 2 presents the theoretical perspective adopted for the study, the reasons for choosing that perspective and the influence it has on methodological choices. Chapter 3 contains a review of the policy context for the study undertaken. Chapter 4 presents a literature review of previous studies analysing low carbon transitions. Particular focus is given to those studies involving adoption of low carbon electrical technologies, including electric vehicles (EVs), distributed generation and heat pumps. In addition, literature on reaction of domestic actors to smart information and small scale smart grid trials is reviewed. Chapter 5 presents a detailed literature review of modelling work using ABM techniques in the electricity sector. In particular, the behavioural and learning algorithms implemented in such models is critically evaluated. Chapter 6 describes the model developed as part of this thesis in detail, which forms the substantive method of research. Chapter 7 describes the case study of domestic PV adoption, including data analysis of existing data on adoption of domestic micro-generation in response to the FiT, which was used for model parameterisation and to inform the discussion of model results' applicability in a wider context. In Chapter 8, the model runs and results are described. Chapter 9 contains an analysis and discussion of the results of model runs. The model results are analysed in combination with the observed adoption based on government data and the implications for policy development and ultimately potential evolutions of the electricity supply system. Finally, Chapter 10 presents the conclusions of the thesis, suggests their implications for policy and strategy with regard to any smart grid implementation and outlines potential further avenues of inquiry highlighted by the work undertaken in this investigation.

Chapter 2

Theoretical frame: Perspective on the transition to a smart grid

As set out in the introduction, this study is aimed toward understanding the role of domestic actors as part of the much larger, complex, electricity supply system during a period of change to a low-carbon smart grid. The primary means of doing so will be a data analysis and modelling exercise to capture relevant elements of human behaviour and their effect on the system. However, in order to draw qualitative conclusions from the quantitative results of the data analysis and modelling exercise, it is necessary to have a theoretical frame describing the whole system within which the model target sub-system plays a part. This short chapter outlines the theoretical frame within which the modelling was undertaken and the form of conclusions that it facilitates.

2.1 Multidisciplinarity

The aims and objectives of the research presented have necessitated a multi-disciplinary approach, as a highly discipline-specific perspective might fail to capture the changes in whole system behaviour. This approach has entailed a study of literature encompassing elements from engineering, simulation modelling, psychology, sociology, economics, policy and Science & Technology Studies (STS). The theoretical framework presented in this chapter outlines the way in which these multiple disciplines have been woven together in order to conduct a study which could achieve the aim of creating a simulation model which gives insight into the effect of human behaviour on the adoption of technology in potential transition to a smart grid, while being relevant to current policy.

This approach to the research presented has necessitated a somewhat longer than usual section on antecedent work and literature review. However, the combination of these literatures is novel and requires exposition.

2.2 Complex adaptive social system

The electricity system might intuitively be described as complex. In this study the term is used with a more restrictive notion of what is meant by complexity, as used in the field of complexity science. Complexity and complex systems do not have a single unified definition. More usually, a series of examples is used to illustrate behaviour which can be considered complex, making it difficult to make an objective way to identify or measure complexity *per se*. Miller and Page (2007) illustrate the fact that the lack of unified definition need not hold back investigation of complex systems, by analogy with architecture where a lack of common definition of architectural beauty has not held back architecture as a whole. A general characteristic is that a complex system consists of elements which interact and through those interactions complex system behaviour results even when the elements behave according to simple rules.

Properties of such systems and their behaviour have been the subject of study in the relatively young discipline known as Complexity Science (see e.g Nicolis and Prigogine, 1989, 1977). Acknowledging the complex nature of a system has implications for the way that scientific study of the system should be approached. Complexity has been described as an emerging or new kind of science (Waldrop, 1992; Wolfram, 2002)

Features of Complex Adaptive Systems (CAS) are distilled by Miller and Page (Miller and Page, 2007), who describe some characteristics of such systems and highlight the advantages of analysis which takes account of these. Important properties of CAS and examples of these within the electricity supply system are given below. It should be noted that the characteristics may appear complex at certain scales (spatial and/or temporal) whereas they may appear linear and "simple" at others.

1. **Irreversible –** in the sense that given the current state of the system, it is not possible (even theoretically), to simply reverse the sign of time and ascertain the state of the system at some arbitrary previous point. The present state of the system is a product of an evolution over time where the history is important to the current state. We see such irreversibility at multiple scales within the electricity supply system – from the network structure of the grid that has emerged over time to the unpredictable coincidence of multiple influences

that can precipitate electricity use in a home.

2. **Emergent phenomena –** these are macro system behaviours that emerge during system operation, but cannot be derived from the description of behaviour of the system components. Classic examples include the oscillation in the Belousov-Zhabotinsky reaction (Zhabotinsky, 1964), or self organisation phenomena such as the Benard cells seen, for instance, if one heats oil in a pan with a little flour in it (Bénard, 1901; Rayleigh, 1916), or the flocking of birds (Reynolds, 1987). In the electricity supply system, emergence can be observed in regular predictable patterns of consumption at a system-wide level that emerge from the individual decisions of millions of electricity consumers every day, even though at the level of individual, or even communities, of consumers, their exact demand pattern may vary markedly from day to day and be very difficult to predict with accuracy.

3. **Irreducible / incompressible –** the system cannot be described in any simpler fashion by spitting it into component parts or subsystems. The number of these components typically makes description by conventional scientific means (such as single governing equations) intractable. This is evident in the electricity supply systems, where the demand on, for instance, a local substation is a result of the interaction of, typically, thousands of consumers none of which can be said to be identical or easily described by a single equation.

4. **Non-linear (often including sensitive dependence on initial conditions) –** As with many systems, the electricity supply system contains both linear and non-linear component elements. For instance, the physical system of cables in the grid is (excepting situations of catastrophic failure) broadly linear in response. However, the demands presented by a device, or building, will typically be highly non-linear, for instance an oven cooking dinner will suddenly demand power when its temperature falls below a certain set point and switch off when it has achieved its desired temperature. This demand is not a linear function of either time or temperature. Sensitive dependence on initial conditions means that a very small change in the initial conditions of the system can lead to very large differences in system state at some time in the future.

The electricity supply system is complex – many stochastic factors combine (e.g. temperature at various points on the network, stock market commodity prices, consumers desires), alongside interactions between components (e.g. wholesale electricity trading, observation of others' consumption habits, fashions for certain appliances) to make the exact behaviour of the system difficult to predict – particularly at longer timescales. That is not to say that we know nothing of how the system will behave – indeed the National Grid and distribution network operators have sophisticated models to predict demand on the network – but we cannot know the detail in advance. While we could know with some certainty which long term contracts might provide the bulk of supply, we could not say, for instance, which exact mix of generators will be providing all the electricity at a specific time even a day or so into the future – that depends on a complex mix of weather and trading conditions.

In addition to being a complex system, the electricity supply system may be considered adaptive – it changes configuration over time in response to both exogenous influences such as political will and endogenous factors such as supply and demand dynamics. Consideration of the electricity supply system from a CAS perspective may be of significant benefit to modelling it (Pfenninger et al., 2014). Work from multiple disciplines can be drawn together to address challenges for the modelling of the electricity supply system – such as the need to increase temporal and spatial resolution to understand the influence of distributed renewable generators and the increasing need to consider the influence of human behaviour in a smart grid.

2.3 Smart grid as a socio-technical system transition

2.3.1 Socio-technical systems

The electricity supply system is treated as a socio-technical system throughout this study. That is to say that social factors (such as economics and the social interactions of individuals within the system) are crucial to the behaviour to the system, as are the technical features of the system (which might include technological artefacts, infrastructure networks, market rules and even, in some definitions, organisational structures).

A definition of a socio-technical system is given below and is adopted for this research:

"At the level of societal functions, a range of elements are linked together to achieve functionality, for example technology, regulation, user practices and markets, cultural meaning, infrastructure... This cluster of elements is called a Socio-technical system"

Source: (Geels, 2005)

This definition fits the electricity supply system well – the system has a strong technical and infrastructural component, user practices and socially determined patterns of consumption strongly influence its operation, and it is governed by extensive regulation. In this study, equal weight has been given to the technical and social facets of the electricity supply system. The reciprocal interaction of the social and the technical aspects are described and modelled, with the technical operation of the system potentially giving rise to changed (social) behaviour in those actors using the system and, of course, with the behaviour of those using the system affecting its technical operation.

In addition to the mixture of social and technical elements characteristic of socio-technical systems, it is notable that there is change in each - for instance the policy changes outlined in Chapter 3. It is therefore appropriate to consider the transition of the electricity network (e.g. to a smart grid) as a socio-technical transition (Bergman, 2009; Grünewald et al., 2012; Verbong and Geels, 2007, 2010; Wall and Crosbie, 2009; Zegers, 2009)

2.4 Transition

The study of transition within STS acknowledges the reciprocal influence that exists between individual actors and the environment or context that they exist within. This idea was by no means invented by this discipline – Systems Thinkers (Senge, 1990), Sociologists (Bourdieu, 1977; Giddens, 1984; Latour, 1987) and Psychologists (Lewin, 1951) *inter alia* had recognised and theorised this before the birth of STS as a discrete discipline.

Consideration of socio-technical transitions, particularly in the Netherlands and often concerning environmental and sustainability, gave rise to a field of study within STS known as Transition Management, which drew primarily on theory from (evolutionary) economics and sociology. Energy system transition, in particular, has been a focus, with a strong emphasis placed on the effects of policy on technology (and vice-versa). In early Transition Management research, ideas of "managing *technology in society*" and *"technology forcing*" (the use of regulation to require technology to meet a certain goal, e.g. emissions standards) were described as an apparently *"attractive option to link science and technology to societal goals*" (Schot and Rip, 1997). Soon afterwards, Strategic Niche Management (SNM) was proposed, where favourable niche developments are nurtured as a matter of policy (Kemp et al., 1998). Whilst such an approach might seem rather unattractive to some as an example of social engineering, in fact the idea of trying

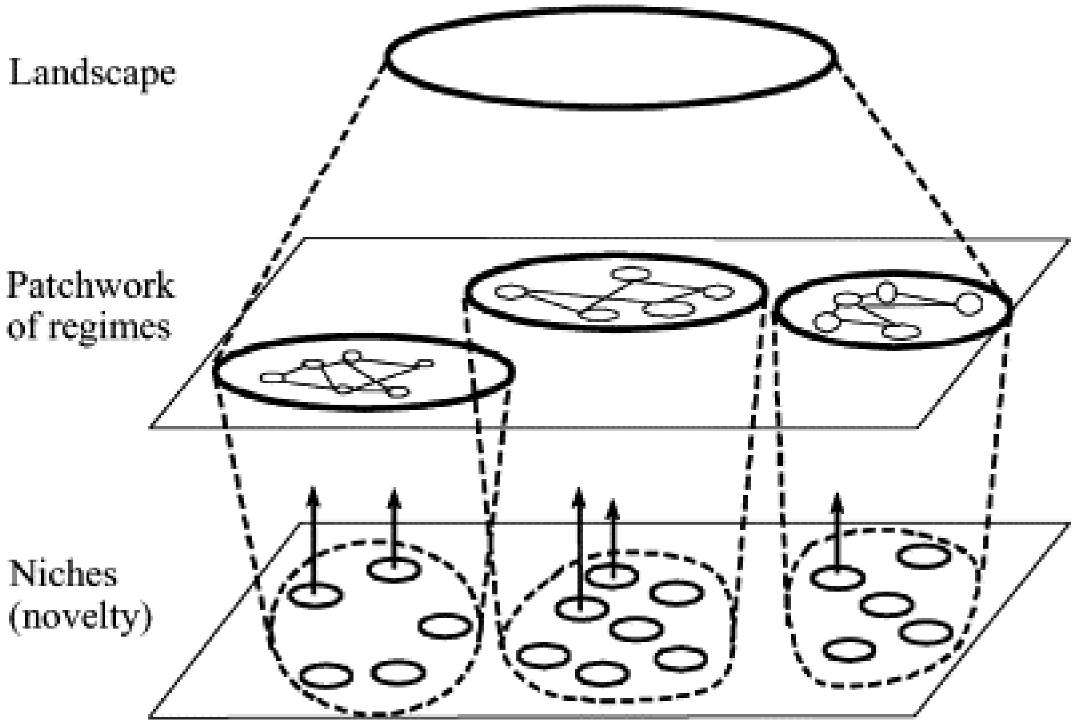


Figure 2.1: The multi-level perspective (MLP).

Source: (Geels, 2002)

to 'pick winners' and encourage a certain group of niche developments has become relatively common in policy, particularly energy policy. Environmental and sustainability transitions have consistently been prominent in the study of socio-technical system transitions e.g. (Berkhout et al., 2004; Geels, 2011; Meadowcroft, 2011; Smith et al., 2005).

2.4.1 Interpreting socio-technical system transition

The multilayered interpretation of socio-technical system behaviour, particularly transition in behaviour and structure, introduced by Rip and Kemp (1998), included from its inception ideas familiar to investigators of complex systems, such as novelty (emergence or innovation) and irreversibility. These ideas were taken forward by Geels and developed into the Multi-Level Perspective (MLP) (Geels, 2002, 2005). The multi-level perspective combined the ideas of socio-technical *regimes* (Nelson and Winter, 1982) and innovative *niches* with the addition of *landscape* (Geels, 2002). Thus, a socio-technical system could be described in a hierarchical fashion (Figure 2.1), albeit with potential for elements at all levels to change over time.

This perspective was proposed as a deliberately integrative framework and defines a hierarchical view of socio-technical systems where *regimes* (combinations of artefacts and modes of operation) are dominant within the more general *landscape*. *Niches* based on innovative technology, combinations of technology or modes of operation may exist and, under certain conditions overtake the dominant *regime(s)*. The perspective is hierarchical in nature, but explicitly expects movement in each level over time, with *landscape* conditions changing and influencing both *regimes* and *niches* such that *regimes* may lose their dominance or *niche(s)* gain a dominant position (Figure 2.2). This perspective, in combination with a typology of types of transition described in its terms (Geels and Schot, 2007) provides a systematic way to describe socio-technical systems in transition. Geels and Schot describe four[1] transition paths as well as a pathway where the socio-technical system is renewed or reproduced – a situation which is characterised by constant incremental innovation (examples for each transition type taken from (Geels and Schot, 2007)):

Transformation: Incumbent socio-technical regimes change under exogenous (landscape) pressure without recourse to one particular niche as niche innovations are not yet sufficiently developed to depose the regime

De-alignment and re-alignment: Existing regimes begin to develop problems and become incoherent or de-aligned. Competition between multiple niche innovations to solve these issues results in the emergence of a winner (e.g. automobiles replacing horse drawn transport in the USA, c.1900).

Technological substitution: A radical niche technology replaces an existing technology when a landscape pressure "shock" occurs in the presence of a sufficiently mature niche creating a new socio-technical regime (e.g. steam ships replacing sail for transatlantic travel under the shock of political revolution and the Irish potato famine in the mid-1800s).

Reconfiguration: Multiple complementary innovations, which developed in niches, are coopted by the regime to solve local problems. They subsequently alter the basic architecture of the regime to the extent that it becomes a new regime, albeit growing out of the original. (e.g. the transition to mass production from batch production in the USA, c. 1900).

Reproduction process: With an absence of landscape pressure the regime will remain dynamically stable and reproduce itself albeit with the potential for incremental innovation.

[1] In their paper on rethinking the MLP, Genus and Coles (2008) add a fifth: "Opening up of a new domain": Successful socio-technical system building provides a new social function. Whilst this is attributed to a Geels and Schot work of 2005, the work could not be found by this author

In addition to this typology, the potential for a sequence of transitions is acknowledged, with systems beginning on one path before switching to another if the landscape is undergoing disruptive change.

Since its introduction, the MLP has been used to describe transitions in a wide range of socio-technical systems (e.g. Geels, 2005) including sustainability transitions (Geels, 2012, 2013)

In the UK, study of transition in energy systems has seen a number of researchers adopting the MLP (e.g. Foxon et al., 2013), sometimes with adaptations, for instance to include insight from practice-theory (Hargreaves et al., 2011). Others highlight the shortcomings of the transition management perspective, criticising the MLP in particular as being mainly useful in a retrospective explanation and lacking predictive power. In Shove and Walker's critique, researchers are cautioned against the apparent homogenisation of method around the Transition Management and MLP models – the authors exhort academics to *"[back] off from the nested, hierarchical multi-level model as the only model in town"* (Shove and Walker, 2007). Genus and Coles offer a direct critique of the MLP (Genus and Coles, 2007) and follow up with a suggestion to rethink the MLP (or at least its application) such that it might be applied more systematically in future research (Genus and Coles, 2008). Responses to these critiques have centred around answering criticism directly (Geels, 2011) alongside a demonstration that using the MLP framework is compatible with a number of ontological perspectives on socio-technical systems and transition (Geels, 2010). One criticism which remains difficult to answer is that the MLP requires decisions to be made regarding start and end dates for transition and what constitutes the system under consideration, this is discussed further as it relates to this study in Chapter 9. This is particularly difficult when attempting to analyse a system that is possibly undergoing transition at the time of the study, as the clarity of a historical view is not available.

Despite these critiques, the MLP has proved to be a useful frame of analysis. The multiple levels allow for a clear definition within a particular project of what is considered to be the (changing) context within which a system operates (the *Landscape*), the set of artefacts and relations making up the *status quo* (the *Regime*) and the characteristics of an innovative socio-technical arrangement (the *Niche*).

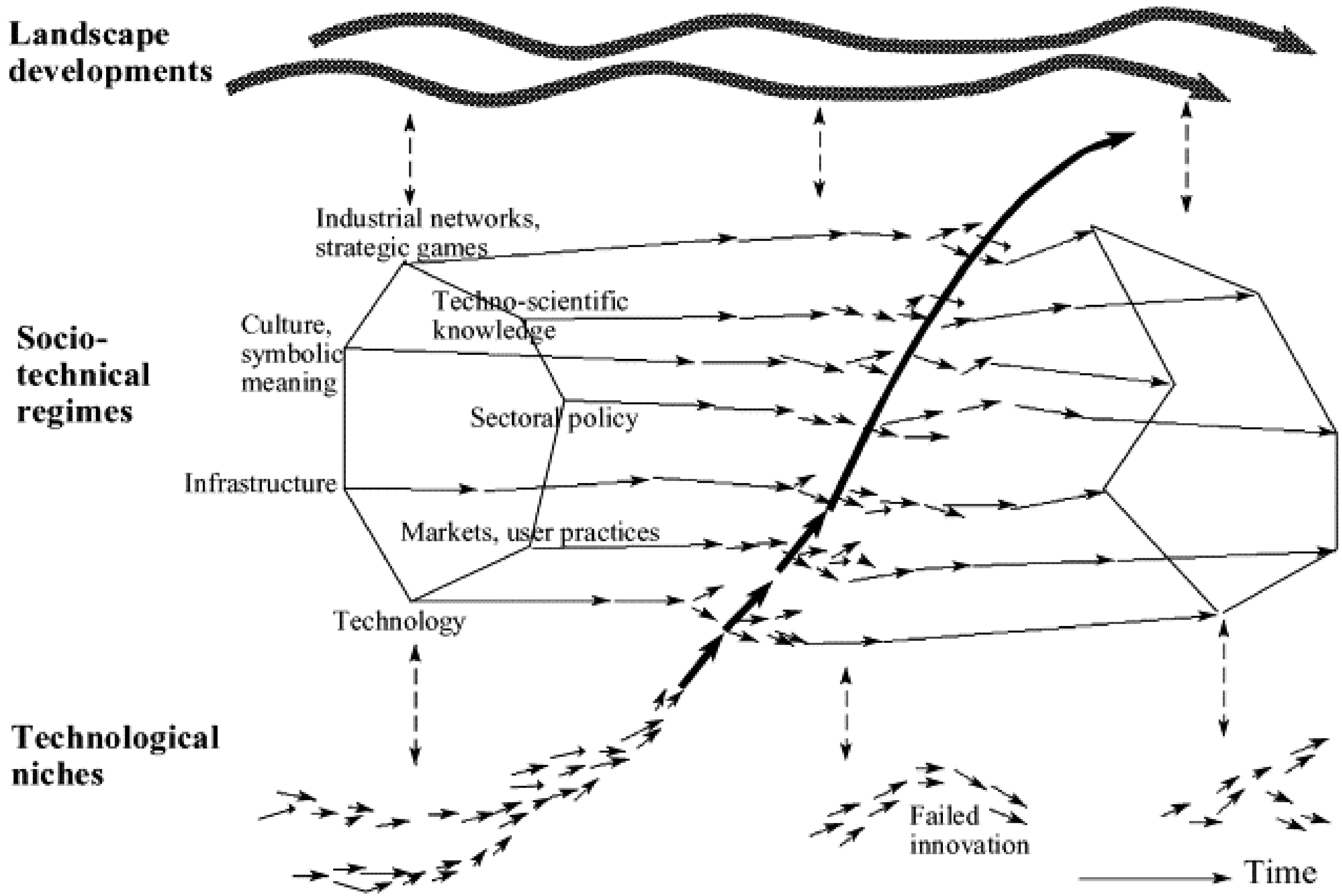


Figure 2.2: Dynamic perspective on transition in the MLP.

Source: (Geels, 2002)

2.4.2 Viewing the change to smart grid as a socio-technical transition

Having described socio-technical transition, this section examines why the change of the electricity supply system to a smart grid can be viewed as a transition. When reviewing socio-technical change in general, Genus and Coles (2008) state that *"Generally, in [socio-technical] research it is argued that transitions commence when: a prevailing socio-technical regime starts to display significant problems"*. In the case of the UK electricity supply system, CO_2 emissions obligations and the associated increase in renewable generation have revealed nascent problems for the prevailing regime of generator control and despatch. In addition, and to some degree in response to carbon obligations, prices of domestic electricity have begun to rise and attracted increased media coverage. Capacity margins have fallen and discussion of the potential for blackouts have become a perennial focus for the media in Autumn (e.g. BBC, 2010; BBC and Robinson, 2013; BBC and Fraser, 2015). Since 2012, Ofgem has produced a capacity report to monitor these concerns, obliging National Grid to provide information on generation mix as the System Operator (Ofgem, 2012) and the latest (published under the title "security of supply report") shows some tightening of the electricity capacity margin to between 0 and 4% and increased uncertainty in the projection of loss of supply hours (Ofgem, 2015, p.10). Subsequent to the publication of that Ofgem report publication, operators of large coal fired power stations Eggborough (2GW) and Longannet (2.4GW) have announced that they will cease production in March 2016, further increasing pressure on the capacity margin. There is no doubt that tightening capacity margins based on the closure of conventional power stations is both a reality and present in the media and public perception of the electricity supply system. All these can be interpreted as signs that the prevailing regime is starting to display significant problems, which could mark the start of a transition.

Another factor involved in transition is a key innovation which can become dominant and unseat the incumbent regime. It is not certain that the smart grid will become the dominant mode of operation for the electricity supply system in the real world – prediction of future state for complex systems is notoriously difficult. However, as this research is set within the context of the smart grid becoming a reality, it will be assumed that it *could* be described as a dominant design, which unseats the current regime.

In the early stages of socio-technical transition, first or early adoption of the transition technology takes place. This is the phase of smart grid adoption that is currently under way and upon which the present research focuses. For instance, adoption of domestic microgeneration, in particular PV, has increased rapidly within the last 4-5 years. Although PV is not a new technology in itself[2], the widespread use of PV panels in a domestic context can be considered novel from a socio-technical perspective.

The end of a transition has been characterised as *"the point when the new socio-technical regime reaches the point where 'social embedding' of the nascent technology/ies takes hold."*(Genus and Coles, 2007). Whether this has yet occurred for PV panels is a question addressed in this work (see Chapter 9), however it is certainly the case that enabling technology for smart grids more generally has not reached this point. Genus and Coles state that *"in order to be considered transitional a technology has typically been identified to be a radical innovation, and to have demonstrated its impact over the longer term (in [reviewed] case studies between 40 and 90 years)."* Again, for technologies fundamental to the smart grid concept this cannot yet be known, but if the promise of smart grids is realised then the innovation will certainly have been radical – with a threefold shift from fossil fuels to renewables for electricity provision; to electricity for heating and transportation; and from passive demand to actively controlled and matched demand. Plans show this transition happening over the next 40+ years (ENSG, 2010).

The preceding section illustrates that a change of the electricity supply system to a smart grid fulfils criteria frequently cited as necessary to describe a change as a socio-technical transition. For this study, such a characterisation is appropriate – the following can be considered to be working definitions for *Lanscape*, *Regime* and *Niche* for the electricity supply system specifically and will be referred to throughout:

- **Landscape –** the policy objectives set down by national government, commodity prices, physical geography, weather and climate.
- **Regime –** the dominant model whereby consumers purchase electricity by quantity from suppliers. Suppliers purchase wholesale electricity from a small number of large generators (mostly fossil fuelled). Energy is supplied "top-down" from the large power stations flowing through a dendritic network to the end user, who may consume the power she needs when she needs it.

[2]the PV effect having been observed in the early 1800s by Becquerel and silicon cells being developed by Bell labs in the 1950s

- **Niche –** socio-technical innovations in the electricity supply system. There may be many niche innovations within the electricity supply system at any one time (as illustrated in Figure 2.1)[3]. In this study, the niche of interest is adoption of smart grid technology whence the erstwhile consumer behaves as a prosumer. The specific niche explored in detail is domestic PV ownership.

The emergence of smart grid as a changed regime would be recognisable as electricity being generated by a mix of existing power stations, large central renewable generation and, crucially, large numbers of small, distributed renewable generators. In addition, tariffs based on generation and use of electricity at specific times of day or in response to specific conditions would characterise such a regime. This thesis concentrates particularly on the adoption of small renewable generators in a domestic setting as the niche of interest.

2.5 Adoption and diffusion of innovation

The study of socio-technical transition has been closely related to studies of adoption and diffusion of innovation. This study is no exception – the influence of human actors on the transition to a smart grid will be that of adopters of innovative technology and consumption practices.

2.5.1 Adopting new technology

Modern study of technology adoption can be traced back to the 1960s, with Rogers' "Diffusion of Innovation" (Rogers, 1962, read in 4th edition, 2010) and Hägerstrand's work on the spatial nature of diffusion (Hägerstrand, 1965). Rogers' work introduced five categories of adopters: Innovators, Early Adopters, Early Majority, Late Majority and Laggards. In Rogers' work, the innovation-decision process is discussed explicitly as passing from the first knowledge of an innovation, through forming an attitude to it to making the decision to adopt or reject. After this, Rogers' theory is that the decision is implemented and then evaluated. (Rogers, 1962). After Rogers, the ideas of diffusion of innovation were developed and given explicit mathematical formulation, particularly from the perspective of study of economics. Bass (1969) produced a mathematical formulation of innovation diffusion:

[3] The smart grid as a niche operating mode might emerge from several niches including innovative relationships between consumers and suppliers (possibly via proxies) to co-ordinate demand to match renewable supply and the technological innovations required to facilitate these relationships.

$$\frac{f(t)}{1-F(t)} = p + qF(t)$$

Where:

$f(t)$ is the rate of change of the installed base fraction;

$F(t)$ is the installed base fraction;

p is the coefficient of innovation;

q is the coefficient of imitation.

This equation will produce the "S-curve" often observed in the total number of adopters of a given technology. The formulation has been used and extended extensively, with notable extensions to account for repeated adoption (e.g. products that will be renewed) (Norton and Bass, 1987) and generalisation to time-varying price (Bass et al., 1994).

These formulations have been found to be applicable over a range of technological innovations and remain a mainstay of studies on innovation diffusion, with empirical evidence being collected and used to determine the parameters for specific cases. Meta analyses have shown the model to have be generalisable and have descriptive power (Mahajan et al., 1995). Such models are used in forecasting and to inform policy, but have been shown to be incomplete in describing adoption patterns in the presence of highly heterogeneous populations, in particular where the coefficient of imitation (q) is highly heterogeneous. Kiesling et al. (2012) find that the lack of consideration of consumer heterogeneity and social factors in Bass models and their derivatives to be a limitation, particularly where a model is required to answer "what-if" questions as this is not the purpose for which the Bass formulation was designed.

Rogers, in his final published paper, considered the network effects characteristic of CAS and how they interacted with Diffusion of Innovations (Rogers et al., 2005). The effect of one off events on the diffusion process [4] was shown (Rogers et al., 2005), demonstrating that, while the basic theory does apply, there is a "fat tail" of residual adoption due to network effects within the CAS and distinct abrupt changes to the curve of adoption due to one-off events that can be considered to occur virtually instantaneously. This reinforces the importance of considering CAS effects to improve upon more traditional diffusion of innovation models where appropriate and we observe that such one off events can certainly affect the diffusion of innovative technology in the electricity supply system (see Chapters 3 & 7). The research described in this thesis approached

[4] in this case the spread of a HIV/AIDS

diffusion of innovation from the bottom up, via behaviour of adopters, rather than using the aggregate methods of the Bass formulation. It will be shown that for the case study, the smooth S-curve of the Bass model is not easily applied (Chapter 7, particularly Figure 7.4)

2.6 Agent-based modelling

Having outlined the theoretical frame for the research conducted, the modelling paradigm used for this research project is briefly introduced. While other paradigms have been suggested to model household level influences on technology adoption (for example social network models (Bale et al., 2014) or choice with multi-criteria analysis (Higgins et al., 2012)), this research was undertaken in the context of an ABM project and hence uses ABM as the modelling paradigm. Here, the applicability advantages of the ABM paradigm for the theoretical perspective is described (in contrast to alternatives where appropriate); the applications of ABM in complexity, socio-technical transition and the electricity sector are reviewed in detail in Chapter 5 and the specific implementation for this research (described in the methods section Chapter 6)

Agent-based modelling is a relatively modern computerised modelling technique. Growing from Cellular Automata research in the mid 20th Century, many quote Schelling's segregation model (Schelling, 1971) as the first example of an ABM[5], particularly when generalised to its two dimensional form. Areas of application quickly diversified with models used to investigate extensions to Schelling's work on population segregation, to ecological studies of organism population, optimisation techniques, economics and others. Latterly, the use of ABM to explicitly provide insight in social science has become more wide spread. The term "generative social science" was coined to describe a series of experiments performed using the "Sugarscape" model (Epstein and Axtell, 1996) and is used to describe ABMs which model the potential behaviour of social systems with the aim of gaining insight into how the target system may behave.

Pedagogical guides to the theory of ABMs and practical development of ABMs have been produced (Gilbert, 2008; Miller and Page, 2007) as the technique has gained acceptance as a useful modelling method.

Gilbert suggests that ABM offers various benefits over other modelling paradigms – these are

[5] some scholars argue that this is a Cellular Automaton, as each agent has exactly the same decision rule and agents are homogenous save for one parameter. It is not important to this thesis to delve deeply into the philosophical distinctions between Cellular Automata and ABMs.

reproduced in the first column of Table 2.1, with a description and relevance for this study added. Miller and Page Miller and Page (2007) highlight a similar list of properties of Agent-based modelling which make it particularly suited to the study of CAS.

Table 2.1: ABM characteristics and relevance to this study.

Source: (after Gilbert, 2008, Section 1.3)

ABM characteristic	**Description**	**Relevance to this study**
Ontological correspondence	The direct encoding of real world entities in the target system is relatively easy to achieve in an ABM.	This study is investigating the effect of real world human behaviour. Ease of encoding observed characteristics into the computer model is paramount.
Heterogeneity	Representation of differing characteristics within the modelled population. This contrasts with many economic and social models, where average or typical values are assigned to all actors in a system.	Studies have shown that predisposition to pro-environmental actions is heterogeneous amongst the population. In addition, social and physical circumstances of potential adopters (e.g. building suitability, available capital) vary amongst the adopting population.
Learning	The changing of characteristics over the time of the simulation (usually to improve outcomes). ABM can model learning at three levels, individuals learning, evolutionary learning where the population fitness improves over time and social learning where agents observe and imitate their peers.	This study will focus in particular on social learning, as observation and imitation of peers is known to be a factor in adoption. In addition, individual learning and adaptation can occur.

ABM characteristic	Description	Relevance to this study
Environment	The environment within which the agent exists can be varied easily – this would be virtually impossible in a real world experiment.	Different policy options are evaluated, as well as different geographical layouts.
Bounded Rationality	Bounded Rationality is based on ideas introduced by Simon (e.g Simon, 1955) and subsequently refined. Agents are limited in the amount of information they have access to about any decision; their cognitive ability and the amount of time they have to process a decision. This can be modelled in ABM, where most economic models assume perfect rationality and information and utility optimisation.	Agents have access to limited information, for example with regard to adoption rates, estimated costs and payback. These are determined from observation of peers and media as well as there own perception.

In particular, as this study investigates the impact of individual decision makers on pathways of transition, the ability of agent-based modelling to cope with high levels of heterogeneity within agents is paramount. As the heterogeneity within agents increases, mathematical models rapidly become intractable. For instance, the Bass model for technology adoption assumes constant coefficient of imitation across the adopting population. Work has been done to introduce some forms of heterogeneity or decision variable (e.g. those reviewed in Bass et al., 1994), or to have coefficients that change over time (e.g. Norton and Bass, 1987). While the Bass model of adoption fits a remarkable number of cases, the fact remains that conventional modelling of adoption is intractable if one wishes to account for and study the effect of heterogeneity within each potential adopting agent. In addition, explicit interaction between agents and with a time-varying environment is often intractable within conventional energy models.

2.7 Overall research approach

The design of the model used in this research and, perhaps more importantly, the analysis of inputs and outputs of the model are undertaken from the perspective of a complex, adaptive socio-technical system analysis as described in section 2.2. The move toward a smart grid is characterised as a socio-technical transition, as laid out in section 2.3. Geels' MLP perspective offers an appropriate and useful frame to this study as it is specifically concerned with the emergence and sustainability (or otherwise) of niche innovations in socio-technical systems. The system is investigated by means of modelling smart grid technology adoption using an agent-based model, incorporating insights from multiple disciplines including engineering, economics and psychology alongside quantitative information from available adoption data.

The model developed seeks to explain observed phenomena and thereby give insight into possible future paths of adoption and the consequences of these for the smart grid as a whole. This is in contrast to models developed to provide (high precision, low uncertainty) quantitative predictions of future system behaviour. The model illustrates possible scenarios – highlighting which appear to be less likely and which more so. The model provides insight into possible effects of policy on householder behaviour on possible paths toward the smart grid.

The case for using models for purposes other than quantitative prediction has been made by Epstein – one of the pioneers of computational modelling and especially agent-based modelling (Epstein, 2008). He first defines the reasons for modelling, arguing that we all model all the time – but that such mental models are often not explicit. Epstein is not the first researcher to note this, however the conflation of simulation modelling with prediction remains in evidence among some energy modellers (Pfenninger et al., 2014). Epstein then offers reasons to design, build and use explicit models – focussing on the tendency of model making to force one to make assumptions clear and explicit and to allow parameters to be easily changed to test model sensitivity. When considering what he calls the reflexive presumption that models should have the goal of prediction of the future *"as in a crystal ball"*, he lays out *"16 reasons other than prediction [...] to build a model."*

A reduced set of Epstein's 16 reasons are particularly pertinent to this research, in particular:

1. The model is used to help explain the system behaviour (Epstein's 1);
2. To shed light on the core dynamics of adoption in this system (Epstein's 3);

3. to discover new questions pertaining to the adoption of technology in the path to a smart grid (Epstein's 5);
4. to bound outcomes to plausible ranges (Epstein's 7);
5. to shed light on core uncertainties in the role of household technology in a future smart grid (Epstein's 8) and
6. to demonstrate trade-offs / suggest efficiencies in policies designed to encourage moves toward a smart grid (Epstein's 10).

In stating outright that the models developed for this study are not used for precise prediction, it is important not to "throw the baby out with the bath water". They may be used to help us anticipate potential modes of operation for the system. Anticipation is not synonymous with prediction. For instance, we might be able to anticipate the possibility of an event, without being able to predict it deterministically – we can anticipate an earthquake along a fault line, but we cannot predict it (e.g. magnitude, precise location of epicentre, time etc.). In the same way, the results of this study may be used to inform discussion of possible modes of system change and operation that we might anticipate, although they are not suitable for predicting precise operational conditions.

With these modelling goals explicitly defined, it is clear that the major conclusions of the model will be qualitative in nature. While the nature of a computational (i.e. numerical) model is that it will give quantitative output, the interpretation of these numbers is preformed in the qualitative domain. Thus, the outcome of the modelling exercise will not take the form of a statement such as *"The implementation of an incentive worth £x over y years will yield a reduction in Carbon emissions of z tonnes"*. Rather, it will take the form *"The system appears to be particularly sensitive to factor x and less sensitive to factor y. Therefore policies focussing on large changes in factor x are more likely to cause z effects"*.

2.8 Summary

The electricity supply system is considered as a complex adaptive social system (2.2) and its transition to a smart grid is examined using Geels' multi-level perspective on socio-technical system transition (2.3 & 2.4). ABM (2.6) will be used to integrate information from data analysis and multiple disciplines to investigate the adoption of technology (2.5) within that transition. The goal of the modelling exercise is to offer insight into the factors affecting technology adoption and how adoption fits into the larger transition to a smart grid. Although the outputs of the model are quantitative, the conclusions that should be drawn from the model developed are qualitative rather than quantitative in nature (2.7).

The following chapter provides the policy component of the current state of the *landscape* for the adoption of low-carbon technology, particularly within a smart grid context. This is followed by a literature review concentrating on transitions within the electricity system, identifying research findings in both existing *regimes* and developing *niches*.

Chapter 3

Landscape: policy review

This study has been conducted in a complex and rapidly changing policy context. The policies and legislation affecting the future electricity network in the UK and, in particular, the transition to a less carbon intensive smart grid are reviewed in this section. These include global agreements on carbon targets, pan-European directives, UK Legislation, national policies, route maps, implementation plans and other documents published by Government departments and local government. Potential paths to a future smart grid as part of a de-carbonised electricity supply infrastructure will be crucially affected by the policies described, the relationships between them and the combination of incentives and regulations that they encode. This section is the result of a systematic review of government websites and documentation, media coverage of policy change and a review of academic literature relating to energy policy. The nature of the UK political system is such that the policy documents in any area are potentially subject to rapid change. This potential has been realised in the case of smart grids, where implementation plans and existing schemes have been subject to major revisions within the period in which this research has been carried out. Several factors have influenced these changes, including a change of Government in 2010 and 2015 and the ongoing impact of the global financial crisis. This has resulted in a subtle change in emphasis within energy policy, which is drawn out below.

A review of media coverage is, perhaps a little unusually, included within this policy review (section 3.3). In the PV case study, the media coverage of policy introduction and changes was significant, meaning that awareness of these factors was high. It is shown later in the thesis that the influence of policy change on adoption rates is significant, therefore it the degree to which the policy was in the public eye and the changes were widely disseminated is a crucial part of understanding the influence of the policy landscape upon the adoption decision. This insight is essential to the discussion of the potential for policy change and awareness to influence future smart grid technology adoption decisions in the domestic context.

3.1 Overview

The starting point for this review was to collate a comprehensive list of UK government policy relating to energy policy and, in particular, the electricity network. For a visual overview of the policy landscape, the reader is referred to the work by ARUP (ARUP, 2016, 2012, 2011), which presents a comprehensive timeline of relevant policies and how they affect the UK. Unfortunately, that poster is not suitable for reproduction in this document, hence the key legislation and policy documents affecting smart grid transition and particularly technology adoption are summarised in table 3.1 and described in this section. The table is organised hierarchically, moving from policies that set targets that provide motivation for moving to a smart grid, through policies and documents that set out how smart grids might be realised, to policies that directly affect the adoption of technology necessary for a smart grid.

Table 3.1: Key UK policies and strategy documents affecting smart grid transition, with focus on PV adoption

Type	**Policy**	**Dates**	**Relevance to this study**
Carbon reduction targets	Climate Change Act (UK Parliament, 2008a)	2008–2050	Legislates for 80% decarbonisation by 2050 and carbon budget mechanism - so far setting reductions of 23% by 2012 and 25% by 2020. This exceeds requirements of Kyoto protocol (UN, 1998) and EU directives (European Union (EU), 2009a,b) and motivates the need for smart grids.
Electricity network contribution to targets	Long term electricity network scenarios (Ofgem, 2008)	2008–	Defines scenarios for decarbonised electricity grid, highlighting the need for smart grids to manage demand alongside intermittent renewable supply at affordable cost.
	Renewable Energy Roadmap (DECC, 4/4/12)	2012–	Defines the planned increase of renewable generation on the electricity network, further underlining the motivation for transition to a smart grid.
Smart Grid Enactment	Smart grid routemap (ENSG, 2010)	2010–2020+	Sets out steps to enacting a smart grid, including pilot schemes funded by Low Carbon Network Fund (LCNF) and rolling out technology, such as distributed generation.
	Smart meter rollout (DECC, 2011a)	2011–2020	The instrument defining how smart meters will be rolled out across the UK. Smart meters facilitate real time measurement of domestic demand and generation. They are the key enabling technology for smart grids.
Domestic PV adoption	Feed-in tariff (UK Parliament, 2008b; DECC, 2009)	2010–	The main instrument by which adoption of domestic renewable electricity generation, particularly PV, is incentivised. This instrument and changes to it are the direct context of PV adoption.

At the highest level, de-carbonisation of the energy supply for the UK is influenced by global agreement (UN, 1998) and European directives to ensure that member states comply with that protocol (including the decision on 2020 targets to cut emissions by 20% based on 1990 levels (European Union (EU), 2009a), directive on renewable sources (European Union (EU), 2009b), the 2030 climate & energy framework (European Union (EU), 2014) and plans for cutting domestic emissions by 80% as part of overall reduction of 50% by 2050 (e.g European Union (EU), 2011). In the UK, targets more stringent than those mandated by the directives have been enshrined into law, with the Climate Change Act 2008 mandating 80% reduction in *total* UK carbon emissions (compared to 1990 levels) by 2050 (UK Parliament, 2008a). Under this Act, 5-yearly Carbon budgets are set in law to define the path to this target, with budget 1 setting a 23% reduction by 2012, and budget 3 setting a 35% target by 2020, for example. This compares to a 12.5% reduction by 2012 mandated for the UK by the Kyoto protocol commitment (the EU as a whole was committed to 8% reductions on the 1990 baseline by 2012 and all parties a 5.2% reduction). Following this legislation, there have been three Energy Acts (UK Parliament, 2008b, 2010, 2011), as well as a further Act that progressed through parliament as the work was undertaken (UK Government, 2013) enacting the Electricity Market Reform (EMR) into law and setting the framework for 2030 decarbonisation targets. A further Bill proposed in 2015/16 with the states commitments to:

" Continue to support development of North Sea oil and gas, to allow local people to have a greater say on new onshore windfarm applications and close the Renewables Obligation scheme to new onshore wind from April 2016. ".

Source: (UK Government, 2015)

In order to meet the legislated commitments for carbon emissions in 2020, there is a clear need to significantly reduce the carbon emissions caused by the generation of electricity in the UK; in the Government's Carbon Plan, the section on low carbon electricity provision commences with the statement *"The power sector accounts for 27% of UK total emissions by source. By 2050, emissions from the power sector need to be close to zero."* (UK Government, 2011). This implies a greatly increased fraction of electricity generation from renewable sources in the UK (commonly referred to as an increased renewable share in the "Fuel mix"), in combination with some Carbon Capture and Storage (CCS) applied to fossil fuel generators, nuclear generation and imported electricity.

The detailed paths to achieving the targets described above are less clearly defined. Work to set out potential scenarios in which the targets are met has been carried out over the last 5-10 years. The 2050 pathways work commissioned by DECC (DECC, 2010d) outlines a number of possible scenarios for 2050 which will achieve the committed Carbon reductions. The work also produced a tool to calculate the impact of various measures across the spectrum of energy use (DECC, 2010a) and a website to allow citizens to design scenarios which met the targets by altering the degree to which each area of energy consumption is changed (DECC, 2011c). This allows a visualisation of various scenarios in 2050, however, very little is reported about how the transition to each 2050 scenario would occur – other than a categorisation of the effort required in each particular initiative ranging from:

"Level 1: assumes little or no attempt to decarbonise or change or only short run efforts; "

to

"Level 4: describes a level of change that could be achieved with effort at the extreme upper end of what is thought to be physically plausible by the most optimistic observer"

Source: (DECC, 2010b)

Looking to the electricity network more specifically, work has been commissioned by both DECC and Ofgem to examine the paths to an electricity generation with vastly reduced Carbon intensity. The Long Term Electricity Network Scenarios (LENS) report (Ofgem, 2008) details five scenarios which range from a highly centralised view of a decarbonised network (*Big Transmission and Distribution*) to a much more decentralised view where large proportions of electricity is generated by small and micro renewable generators (*microgrids*). The former approach would be driven by investment in nuclear power stations and large scale renewables (such as onshore and offshore wind farms, often cited as *"Big Wind"*) while the latter envisages, for instance, householders investing in domestic generation such as PV, potentially owning storage devices and using electricity more efficiently.

The LENS report sets out some of the necessary actions to bring about a transition to the scenarios it describes, however detail is still lacking. Some efforts have been made to flesh out some of this detail. In 2010, the Electricity Network Strategy Group(ENSG) produced the "Smart Grid Routemap", a report setting out potential paths toward a smart grid (ENSG, 2010). This sets out some necessary steps toward a smart grid future and highlights the need for pilot projects, outlining some potential sample projects. However, this routemap is still unclear how the necessary adoption of devices to facilitate a smart grid will occur. In a section on Distributed Energy Resources (DER), defined in that document as "Distributed Energy Resources (demand response, storage and distributed generation)", it is noted that:

"A particular challenge exists around the customer value proposition linked into technical control and automation and DER commercial frameworks and incentives"

Source: ENSG (p. 15 2010, Challenges to DER)

A number of initial steps have been taken along the road toward a smarter electricity network. A key enabling technology for any transition to a smart grid is the installation of smart meters and communications infrastructure to allow the regular collection of electricity usage data (smart metering) and the feedback of information, potentially coupled with price or intelligent control signals, to the consumer. The legislation to allow for smart metering to be installed has been passed and various statutory instruments have been passed to allow for the processing of the data that they will provide (UK Parliament, 6th November 2012). The EU and UK legislation relevant to smart metering, along with a description of the consultative process and the relevant non-legislative policy documents are summarised in a Scientific Note prepared for the Commons Library (Commons Library, 2013). The implementation plan for smart metering roll out originally planned to start with smart replacements in a small number of homes in 2012, before entering the mass rollout phase in Q2 2014 and completing by 2019 (DECC, 2011a) – this is now planned for Q4 2015 with completion around 2020 (Davey and DECC, 2013; DECC, 3rd July 2013). The recent Energy Efficiency Directive (European Union (EU), 2012), has content relating to smart meters, with the specific requirement that *"domestic consumers should be provided with easy access to at least 24 months of daily/weekly/monthly/annual consumption data, where they have a smart meter"*. This may require a change in the regulatory framework for smart meters in the UK, which has triggered another round of consultation.

Another key component of the smart grid vision, and the main subject of this thesis, is the widespread adoption of distributed renewable generation. The Renewable Energy Roadmap produced by DECC (DECC, 4/4/12), describes the way that the UK wishes to introduce renewables into the fuel mix. The FiT, introduced in the Energy Act and coming into force in April 2010 (UK Parliament, 2008b), has encouraged the adoption of distributed renewable generators, particularly domestic (mainly rooftop) photovoltaics.

3.2 Feed-in tariff policy

A key source of data pertaining to the FiT is the impact assessment prepared as the policy was being designed (DECC, 2009). This document sets out the basis for calculating the tariff offered and the methods used in modelling predicted uptake. The impact assessment considers four scenarios using an economic cost-benefit model to provide data on their likely consequences. Three of the scenarios considered supported domestic microgeneration ("Lead scenario", an "8% ROI" scenario and a "community scenario"), while the fourth ("non-microgeneration") assessed a tariff supporting only larger installations. In outlining the motivation for the FiT, the first objective is stated to be:

"The objective of FITs is to contribute to the UK's 2020 renewable energy target through greater take-up of electricity generation at the small scale and to achieve a level of public engagement that will engender widespread behavioural change."

Source: DECC (2009, p. 6)

The tariff eventually implemented for retrofit PV (<=4kWp) was 41.3p/kWh - between the level suggested by the "'8% ROI" scenario (59p/kWh) and the "Lead" (and recommended) scenario (36.5p/kWh), which assessed deliberately reduced PV tariffs due to the ease of PV deployment compared to other technologies. The projected impact of the "Lead" scenario was:

"The scenario is projected to deliver 870,000 renewable installations by 2020, generating approximately 6TWh of additional (to the baseline) 9 This means that domestic PV installations do not require planning consent. 11 electricity in 2020 at a resource cost of £600m in 2020 (annual), £8.7bn cumulative to 2030"

Source: DECC (2009, p. 11)

This was further broken down by investor type, with the "Lead" scenario projected to incentivise around 50,000 domestic installations over all technologies by mid 2011, with adoption following an "S-curve" to the 2020 target.

The policy was undoubtedly successful in encouraging the adoption of domestic (rooftop) solar photovoltaic generators. In fact, the policy was deemed so successful by the government in mid 2011 (at which time some 70,000 installations were registered compared to the projected 50,000 or so), that an extraordinary review of the policy was ordered and a subsequent reduction in tariff mandated, despite the fact that the first review was originally planned to make changes for implementation in 2013. Although the decision to reduce the tariff was successfully challenged in court (EWCA Civ 28, 2012) and parliament (Hansard, 2012), the net effect of that challenge was simply to delay the reduction, which was enacted in March 2012. Since 2012 there have been several rounds of tariff cuts, including a change to the mechanism by which degression was implemented, eventually resulting in a process of three monthly tariff review. Toward the end of the research presented, another consultation commenced (DECC, 2015b), with the policy under discussion being to cut the rate for rooftop PV to 1.3p/kWh, a large change from the rate implemented in April 2010 (43p/kWh in today's terms allowing for inflation). The effect of the FiT and changes to it on patterns of adoption form the central theme of this thesis and the data on observed adoption is analysed in detail in Chapter 7 before being discussed fully in Chapter 9.

Other policy also has some bearing on the likely transition paths toward a smart, decarbonised electricity network. The economic aspects of the transition toward a decarbonised electricity network are affected by the Electricity Market Reforms, which have been widely consulted upon (DECC, 2010c). During the course of this research, the Bill was enacted into law (UK Government, 2013). Although these reforms affect the wholesale market and have little to say about the retail tariffs on which so many smart grid visions are predicated – they nonetheless affect the landscape for a transition toward a smarter grid. The contracts for difference and capacity market elements of the proposed reformed market will affect the business cases for investment in large scale renewables significantly. Uncertainty remains regarding how (aggregated) consumers with domestic microgeneration and/or demand side response capability (i.e. the potential to offer negative demand, largely similar to generation) could participate in the capacity market that the EMR introduces (Warren, 2014). In addition, Ofgem's ongoing retail market reviews (Ofgem, 19th April 2013) will affect the possibilities and incentives for innovative retail tariffs to be introduced.

Prior to 2015, the main two instruments encouraging the installation of renewable electricity generation have been the Renewables Obligation (RO) and the FiT. The RO has been available since 2002 (when it replaced the Non-fossil fuel obligation, which had been available since 1990). FiT is available for installations with capacity less than 5MW, whereas RO largely supports projects with a capacity greater than 5MW. Following the EMR conclusions, RO is to be phased out in favour of Contracts for Difference (CfD) as the main instrument to encourage renewable generation.

3.3 Media reporting of policy and policy changes

An important component of the public perception of the policy landscape is the media reporting of such policy. The slippages and apparent shortcomings of certain policies have been the subject of rather negative reporting, including the smart meter rollout e.g. (BBC, 2013a) and the Green Deal (e.g BBC, 2013b). In contrast, the FiT policy received some broadly positive headlines as it was announced (e.g. Bachelor, 2010), with some evidence that there was broad public support for the measure (Seager, 2010). There was extensive media coverage of the initial extraordinary tariff review at various stages – before it came into force (e.g Clark, 2011), the (successful)[1] challenge to the legality of that review outcome (e.g Harvey and correspondent, 2011) and immediately after cuts eventually came into force (e.g. BBC, 2012; Which? Energy, 2014). This widescale coverage served to advertise the fact that a generous incentive was likely to be reduced. This has been followed, albeit to a lesser degree, by some media coverage of the later degression reviews (e.g. Murray and Shankleman, 2015; McGrath and BBC, 2015). Since 2012, the prevailing media narrative has been one of reporting the decline in the (domestic scale) PV industry in the face of ongoing cuts to the FiT (Morris, 2012). The further steep cuts to the tariff proposed for 2016 have seen some coverage, particularly in the face of some large domestic PV installation companies ceasing operation, but this coverage has not had the same intensity as the coverage in 2011. The trends in public interest around this issue are illustrated by the trend in web searches for the term "UK FiT" over time (Figure 3.1)

[1]The details of the details challenged and ruling are covered by EWCA Civ 28 (2012)

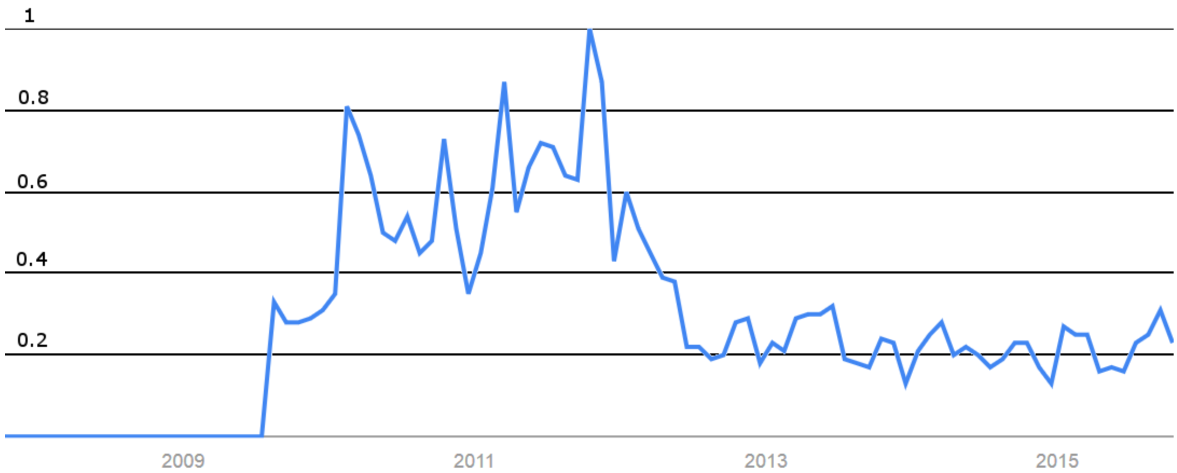


Figure 3.1: Normalised trends of web searches for "UK feed in tariff" over time on a popular web search engine.

Source: Google Trends (www.google.com/trends)

The media coverage of energy policy shows an increasing focus on issues of energy prices, fairness (in terms of energy poverty and access to energy as well as in terms of fairness of the retail prices offered by energy supply companies) and security of supply. These observations lead to the conclusion that energy policy in general appears to be gaining increased media attention and it is therefore likely that any transition to smart grids will be subject to similar scrutiny and the effects of that scrutiny. An early example of the media influence on behaviour in the UK smart grid transition is evident in the analysis of adoption data in reaction to the FiT policy presented in Chapter 7.

3.4 Political change

There is some evidence that the speed of deployment of some household energy saving and generation measures is being affected by a change of emphasis in energy policy following elections in 2010 and 2015[2]. The tightening of financial constraints due to ongoing effects of the global financial crisis in 2008 and a different view of the relative role that state controlled change should play as compared to market forces have combined to alter energy policy. The changes in combi-

[2] In 2010, the Labour government was replaced by a Conservative and Liberal Democrat coalition government, followed by a majority Conservative government in 2015

nation appear to amount to a change in focus. For instance, the FiT has been the subject of an extraordinary review to reduce the level of incentive beyond the originally planned degression (Hansard, 2011), with studies asserting that this will increase uncertainty and potentially inhibit further adoption of domestic PV generation (Muhammad-Sukki et al., 2013).

In addition, the Carbon Emissions Reduction Target (CERT) and Community Energy Saving Programme (CESP) schemes have been replaced with the Green Deal (DECC, 2012), which relies on market mechanisms to a far greater degree with a corresponding reduction in money available to householders to introduce energy saving efficiency measures (Guertler, 2013). More recently, funding for the Green Deal finance company has been withdrawn and the householder improvement fund closed to new applications, apparently leaving the scheme as an assessment framework only, with no government funding for energy efficiency improvements in the home (DECC, 2015a).

The uncertainty and reviewing of policies related to smart grid and enabling technology continue. On the technical side, FiT levels continue to be reviewed three monthly, and evidence from other countries suggests that more change may be in store – as Spain now charges consumers for self-consumption of locally generated electricity and Germany is considering doing the same (BMWi, 2014, read in translation). In addition, the UK Prime Minister recently announced a review of all "green tariffs" that may add cost to domestic energy bills (EurActiv, 2013), reportedly branding them "green crap" (Guardian, 2013). A further radical reduction in tariff is being consulted upon in 2015.

3.5 Summary

The above review of policy affecting the (potential) transition to a smart grid in the UK describes a complicated and interleaved portfolio. An analysis of the strategic reports and implementation plans for decarbonised and smart electricity grids show that almost all have some common elements. In particular, they all envisage a shift towards electricity as the primary fuel for heating in buildings[3], which will necessarily increase the load on the electricity network. The strategies also envisage an increasing proportion of transport being via electric vehicles. This provides an economic case for a transition to a smart grid, as smart use of the network could result in multi

[3]The envisaged shift to electrical heating is additionally supported by district heating / CHP fuelled by biomass and waste DECC (2013c)

billion pound savings relative to a naïve reinforcement of the network in a business as usual fashion (Pudjianto et al., 2013). In addition, a political case for the transition to smart grids is being generated in the EU, where directives mandating decarbonisation, smart metering and energy efficiency oblige the UK to move at least some way toward a smart grid. Thus, it is reasonable to conclude that the transition to a smart grid is an intended outcome of the policy landscape.

However, the description of the changing policy landscape in this chapter underlines its dynamic and uncertain nature. Policies designed to encourage smart grid transition are subject to even larger scale changes such as political change at general elections and the global economic crisis, both of which have caused change even during the course of this research.

This study is motivated by the lack of description of how the behaviour of those who use energy will contribute to, or detract from, the progress along any of those paths toward a smart grid. Policy is designed to affect the behaviour of companies, households, communities and individuals within the UK. However, it is not obvious that explicit financial incentives (such as that provided by the FiT) will be sufficient to prompt all of the various changes required in order to meet the expectations of those policies. There is a considerable degree of uncertainty both in the policy changes which may occur and the reaction of individuals to that uncertainty.

The policy which directly provides context for this study is the UK FiT. This is a policy designed specifically to incentivise adoption of distributed small scale renewable generation – a key component of most smart grid scenarios. The pattern of citizen reaction to this policy will give insight into the way that human actors react to policy.

There is a growing literature on the subject of modelling energy systems under various policies and, in parallel, on behavioural change as a component of energy efficiency, energy demand reduction and energy demand management. Both of these literatures are reviewed in the next chapter. However, the combination of the two has been he subject of little attention thus far.

The combined application of a computer simulation model incorporating the behaviour of agents to the investigation of transition paths in the context of the complex policy landscape reviewed in this chapter is an area which has yet to be explored. The benefits of this approach to understanding policy impact has motivated this study and led to the development of the model described in Chapters 6 and 8.

Chapter 4

Literature review

Due to the multi-disciplinary nature of this research, the literature reviewed is drawn from various disciplines including Science and Technology Studies (STS), economics, psychology, sociology, computer science and engineering. To aid in the organisation and presentation of the review, the literature has been broken down into a number of sub-sections: study of transition in energy systems (Section 4.1); differences envisaged between the present system and a future smart grid (Section 4.2); research into domestic consumption in the context of a smart electricity system (Section 4.3); studies of technology adoption (Section 4.3.2). A short synthesis of these sections, outlining the conclusions and limitations of work that precedes this research project is provided in the final sub-section (Section 4.4).

4.1 Transition in energy systems

Although transition to a smart grid is a recent concern, transitions in energy systems more generally have received increasing research attention over the past two decades. Prior work in general energy systems transitions is reviewed first, followed by investigations of the electricity supply system in particular and finally study of transitions to a smart electricity grid.

4.1.1 General

Study of transitions in energy systems are predicated upon the acknowledged need for transition to a low-carbon or sustainable future state. The concepts of socio-technical regimes of operation alongside the landscape and niche concepts expressed in the MLP have been prominent (Chapter 2). Other approaches have been used or combined with these, for instance innovation network concepts have been integrated (Steward, 2012) and transition has been studied from a Practice Theory perspective (Shove and Walker, 2014; Berkhout et al., 2004). Hughes and Strachan (2010) review methods used to produce scenarios and study transition pathways and note the lack of consideration given to co-evolution of various factors in a low-carbon transition as well as the lack of a clear representation of actors. This project aims to contribute toward addressing these limitations of previous work. The prospect of transition to a sustainable future remain an active area at the frontier of transitions research, as developments continue to unfold such as the increased prominence and economic attraction of shale gas (Cook and Langendahl, 2013); the various changes in attitude to nuclear power (Rosenbloom and Meadowcroft, 2014) and the financial crisis (Geels, 2013). The landscape is far from settled.

4.1.1.1 Computer models of transition

Studies of transition have sometimes included formal (mathematical or computer-based) models to inform the analysis and add insight. ABMs have been present alongside systems dynamics and some mathematical differential equation based models. The most full featured transition ABM to date is the MATISSE model, implementing an extended MLP with agents representing regimes and niches allowed to exist, grow, replace and die whilst rather simple population agents represent individuals, initialised with preferences and drawn to their nearest regime or niche (Haxeltine et al., 2008; Schilperoord et al., 2008). One review notes that the models reviewed offer a high level view of transition and that specific, localised models are needed (Holtz, 2011). In particular, it is notable that the role of individual actors' internal decision making process in adopting technology is absent in these models – the frameworks instead concentrating on the aggregate level. The current study uses a localised model, informed by nationwide data analysed on a local level to study the potential for transition under implemented and proposed policy landscapes.

4.1.2 Transition in the electricity supply system

Within the study of whole energy system transitions, researchers have identified the electricity supply system as a subject for study and it accounts for a large proportion of CO_2 emissions e.g. (Hammond and Pearson, 2013). There is little doubt that electricity supply systems have already seen transition. Shackley and Green use the MLP to characterise a number of transitions in the UK electricity supply system, viewing the 1980/90s 'dash for gas' as a transition taking the form of resource substitution in the context of a change of political landscape including privatisation and liberalisation of the formerly nationalised industry (Shackley and Green, 2007). Comparisons are drawn with the Dutch electricity system, where Verbong and Geels found an ongoing transition under way, with roots in market liberalisation and European harmonisation (Verbong and Geels, 2007). Both studies note that the electricity supply system was relatively stable prior to liberalisation (although neither consider the transition that occurred as the network itself was established – highlighting the dependence on chosen timeframe for the results of transition analysis). Most recently, using the case of Ontario, a study of transition in electricity systems encompassing the entirety of its history has found that the move toward decarbonisation is likely to be politically driven and that it is important to consider transition of the electricity system within the context of broader energy system low-carbon transtion (for instance introduction of low carbon transport and district heating) (Rosenbloom and Meadowcroft, 2014). The MLP is used as a frame, although Meadowcroft's previous criticism of its lack of explicit consideration of the politics surrounding transition is repeated and the article concentrates on the political drivers of regime change.

Verbong and Geels characterise the move towards more distributed generation a de-alignment and re-alignment transition. This implies large and sudden landscape change (such as dramatic shift of energy policy in this context) causing de-stabilisation of the regime and opportunity for niche innovations. They note that a smart(er) grid is necessary for any envisaged change to a low-carbon electricity system, but is most crucial to the de-/re-alignment pathway including increased distributed generation (Verbong and Geels, 2007, 2010).

In the UK, characterisation of future transitions to an electricity supply capable of meeting 2050 low Carbon goals has been put into conceptual categories (Foxon et al., 2010) and developed into three pathways (Foxon, 2013). These pathways are

1. **Market Rules** - Market logic is dominant, low-carbon achieved by centralised nuclear, Carbon Capture and Storage and wind. Current regime actors remain.

2. **Central Control** - Government logic is dominant, with regulation becoming more important and similar centralised low-carbon technologies.

3. **Thousand Flowers** - A highly decentralised vision, large quantities of distributed generation and with most reliance on a smart grid.

The pathways have been also been considered as a series of critical branching points, illustrated via a detailed comparison with the historical transition to supply of gas to homes (Foxon et al., 2013). This research highlights the potential for the timing of critical events and the limitations they impose to cause the system to become locked into a certain pathway, or to preclude one. For the Thousand Flowers scenario critical events considered include the potential for the required rate of distributed generation adoption contributing to failure of the pathway as the actors become overloaded by the amount of change required. This is an possibility relevant to this study as possible rates of adoption are examined.

Whilst transition pathways have been described and typologies of transition produced, they provide only the framework for a systematic study of a transition that is, or may be, taking place. The detail and dynamics of the transition itself remain an open area for study, to which this project contributes. As Verbong and Geels put it:

"...these tools cannot predict *the precise development of future electricity systems, they can enhance the analytical depth and reflexivity in policy making, especially by explicating the dynamics of transitions and by opening up the (often hidden) choices at the third policy (paradigm) level of general goals and strategies."*

Source: Verbong and Geels (2010)

In general, the role of the individual actor in socio-technical transitions has been given less attention than the larger scale influencing factors and measured changes. However, Nye et al. take a socio-psychological perspective on the subject, developing *"a framework for analysing the roles of domestic actors in the transtion to a lower carbon electricity economy."* (Nye et al., 2010). They concentrate on the influence of domestic actors through repeated behaviours and consumption habits, rather than as adopters of new equipment, concluding that:

"Our analysis confirms what is becoming an increasingly common position within policy and practical circles: that shifting to more sustainable patterns of consumer electricity demand is as much about a shift to more sustainable lifestyles as it is about the adoption and diffusion of new, lower carbon technologies."

Source: (Nye et al., 2010)

The basis on which the words *"as much about"* are used is not clear and could be viewed as contentious given the relatively small changes observed in an experimental settings due to behavioural measures alone (see section 4.3). However, they draw attention to the importance of socio-psychological factors in low-carbon technology diffusion – an insight that is incorporated into the modelling and analysis in this study.

The literature reviewed in this section shows that there is interest in study of transitions to a low-carbon electricity supply system. Some view this as being under way, for instance citing some evidence for divergence from the "locked-in" trajectory of reliance on fossil fuels (Carley, 2011), while others characterise the transition as remaining in the future (Foxon, 2013). All note the crucial importance of policy goals in shaping such a transition. There is a lack of transitions research into the current response to policy incentives for adoption across a range of low-carbon technologies and how that response may be viewed as part of a system wide low-carbon transition . This is a gap which this study fills. Most studies acknowledge the necessity of a smart(er) grid in these transitions, however it is further notable that a transition to a smart grid *per se* is absent from the majority of these studies. The research that has addressed smart grid more directly is considered in the next sections.

4.1.3 Transition to the smart grid

Where the transition to smart grid has been studied, it has usually been discussed as a small component of a transition to a low carbon grid, for example in Foxon's work described in the previous section (Foxon, 2013). The smart grid and smart metering are given only one line in the description of the scenarios: *"'smart grid' technologies are needed to meet increasing amounts of distributed generation"* in Market Rules and Central Coordination, with a slightly more ambitious *"50% distributed generation requires development of 'smart grid' technologies to handle two-way power flows"* in the decentralised 'Thousand Flowers' pathway (Foxon, 2013). Foxon highlights key risks to the smart grid dependent pathway:

- **Difficulty in adopting** distributed generation.
- **Rebound effects**, where savings made are used to increase overall demand.

The model developed in the present research project contributes toward investigating these risks and their effect.

Verbong et al. (2013) consider the transition to smart grid directly. They highlight the importance of considering the (implicitly domestic) user when designing policy intended to promote the transition to a smart grid – in particular advocating learning about social dimensions as well as technological to avoid lock-in to a particular transition pathway.

In other disciplines active in smart grid research, transition is more implicit in the study than the object of the study in itself. For instance, technology adoption has been studied in economics (see section 4.3.2), but usually under rather strict conditions of *ceteris paribus*, working from the assumption that a homogenous population will reach an optimum supply-demand equilibrium under the action of a free market, considering a snapshot in time rather than from the perspective of being a component in system transition to a different operating mode.

There is a strong theme of smart grid research in electrical engineering that considers a transition to a smart grid as a technical change in order to mitigate the effect of electrification of transport fleets and heating sectors as part of overall de-carbonisation strategies (Gan et al., 2011; Pudjianto et al., 2013). Engineering research also focusses on snapshots in time, sometimes under a number of different scenarios of system change, and evaluate the impact from an engineering point of view once the change has occurred – human agency is absent or considered only implicitly encoded as a demand profile. Where transition is explicitly mentioned in this discipline, research identifies new roles such as prosumer and new technologies that will be present in a smart grid, but does not consider how the change to a grid comprising these elements may occur (e.g. Favre-Perrod et al., 2009). In particular, the concomitant social and cultural changes that will be necessary to embed the new technology and roles are barely referenced beyond broad economic incentives. The dynamics of how the change occurs (over the timescale of years) is not addressed.

This review shows that the transition to a smart grid has been referred to as part of a low-carbon transition and been implicit in research on smart grid economics and technology. Pathways to a low carbon electricity system have been studied, but research into pathways of transition to a smart grid in particular are largely absent. In general, research on smart grid futures has centred around the definition of what a smart grid scenario will be. This is not surprising – a vision of or expectation of future state has been described as intrinsic to social action and, therefore, that the production of such visions is inevitable for any innovation (Berkhout, 2006). For Berkhout, these visions are actor and context specific, in some contrast to the usual transition perspective of a collective, shared vision or goal. The method employed in this research allows for individual expectations of adopting a particular innovation to be maintained (albeit limited by their encoding as a number of variables in a computerised model) and examines whether a collective vision, articulated by stated policy goals, is achieved. The next section describes the work to date on smart grid visions.

4.2 Visions of the smart grid

This section describes studies that produce static future scenarios in contrast to the previous section considering transition toward them. The vision of a future smart grid is far from singular. A recent report for a major UK Research Council review and scenario development project in the UK (www.smartgridscenarios.org.uk) begins with the observation that:

"Smart grids are expected to play a central role in any transition to a low-carbon energy future, and much research is currently underway on practically every area of smart grids. However, it is evident that even basic aspects such as theoretical and operational definitions, are yet to be agreed upon and be clearly defined."

Source: (Xenias et al., 2014).

A number of research projects have focussed upon projecting scenarios for future low carbon energy scenarios for the whole energy system. Smart grid components have been present in the more recent studies, smart meters are noted as essential in the four scenarios developed as part of government's foresight report (Foresight, 2008; Foresight and Technology, 2006) and the 2050 scenarios for the electricity network (Ault et al., 2008; DECC, 2010a). Gradually more holistic ideas of smart grid – encompassing consumer interaction, distributed generation and electrical transport and heating – have been included rather than simply smart meters (DECC, 2010a; Foxon, 2013; National Grid, 2013)

In the most recent project of this kind, (Balta-Ozkan et al., 2014), a variety of expert opinion was combined to produce scenarios for the UK smart grid, including some pathway steps necessary in order to achieve each scenario. The scenario construction methodology used was Field Anomoly Relaxation (FAR) – used as it does not constrain the number of scenarios produced. Four scenarios emerged:

1. **Minimum Smart –** substantial amount of flexible generation, passive customers, smartening only as and when required.

2. **Groundswell –** strong and growing interest in energy efficiency from customers, adoption of distributed generation, new market entrants in supply and aggregation, policy led by public interest.

3. **Smart Power Sector –** consumers passive, policy led development of renewable resources, innovation led from network operators, supply-side adoption of smart technology.

4. **Smart 2050 –** strong and sustained policy commitment to renewable energy, engaged and active consumers, capital available at competitive rates.

Of these, the Groundswell and Smart 2050 scenarios contain the domestic demand side response and device adoption considered in this project. The Groundswell scenario is congruent with the smart grid element of Foxon et al.'s Thousand Flowers electricity system transition. A number of workshops were conducted after the development of scenarios to understand the individual and social impact of these scenarios. These found that Groundswell was by far the most popular, with Smart 2050 next most popular, although it should be noted that the Workshop participants had rather strong levels of interest in aspects of the smart grid before the workshop (Balta-Ozkan et al., 2014) Table 5, which suggest that the participants may have been somewhat self-selecting, which in turn may influence this preference.

Engineering overviews have been provided, with estimates of monetary savings from implementing smart grids as compared to using traditional (Business as Usual) methods of maintenance and enhancement ranging from £8-20bn (Pudjianto et al., 2013).

Despite a lack of precise definition of any future smart grid, a number of common themes do emerge in the literature. These include:

1. The availability of near-real time information about the consumption of any grid user and the state of the grid itself.

2. The sharing of real-time usage information in order to optimise the matching of supply and demand.

3. A far greater proportion of electricity being generated by renewable sources.

4. Substantial movement of the transport fleet and heating sector to electricity.

5. A greater penetration of embedded renewable generation distributed around the grid.

6. The participation of demand to match supply, rather than the traditional methods of simply altering controllable (dispatchable) supply to match demand.

A very common, although not ubiquitous, feature often allied to 2. above is time dependent pricing of electricity consumption – referred to as real time pricing (RTP) where changes happen quasi real-time, or Time of Use (ToU) pricing where time is divided into periods of several hours with different pricing.

In this study, 1. & 2. are taken as likely to occur as the UK government has a policy to roll out smart meters capable of both transmitting the information required and receiving information about the system state as a whole (Davey and DECC, 2013). The potential transition to this situation has received academic attention, with the merits of various strategies being evaluated (Zhang and Nuttall, 2011).

Item 3. can happen at various scales, but as this study concentrates on the domestic scale participation in the smart grid, further literature analysis concentrates on 5. (a greater penetration of embedded renewable generation distributed around the grid and) & 6. (the participation of demand to match supply, rather than the traditional methods of simply altering controllable (dispatchable) supply to match demand.

4.2.1 Embedded / distributed renewable generation

Views of the smart grid generally encompass renewable generation which is connected to the distribution network (embedded) and consists of many small generators spread through the network (distributed). This feature of future smart grids has received considerable attention from the electrical engineering point of view (Lidula and Rajapakse, 2011; Lilley et al., 2012; Platt et al., 2012; Pudjianto et al., 2007). In these studies, the vital effect of intermittent unpredictable (micro)generation on networks is given rigorous treatment, bu the behaviour of their owners or operators is absent. In their assessment of the potential to balance widespread PV adoption with local CHP and storage, Balcombe et al. (2015) note that the National Grid may start to encounter problems in transmission network operation if PV capacity exceeds 10GW, although the National Grid document is worded in the reverse *"Up to a penetration of around 10% of households or 10GW of generation, solar PV can be accommodated on the system without making the operation of the transmission system significantly more difficult."*

Source: (National Grid, 2012).

Multi-Agent systems (closely related to ABM) have been proposed as one method to integrate embedded renewable generation in a smart gird while providing demand-side management capabilitites (Kok et al., 2010, 2006).

4.2.2 Managing embedded renewables via demand-side management / response

Demand-side management (DSM) is a technique which could deal with the integration of high penetrations of distributed energy generators via owner behaviour (at least in part). As such, the literature on DSM is intrinsically linked with adoption of low carbon microgeneration as well as smart grid technology more generally. Demand side management has attracted attention in engineering (Kok et al., 2005; Openshaw, 2010; Pudjianto et al., 2013, 2007; Strbac, 2008), economics (Faruqui et al., 2007) and sociology (Wilhite, 2008; Wilhite et al., 2003). The concept is simple to describe, but almost certainly complex in implementation. In essence, it refers to enticing, or in some cases instructing, a consumer to change their demand in response to a request (or command) from a centralised entity that has an interest in changing the aggregate demand (either a supplier, or a system operator).

The form that the request takes could take multiple forms. To some degree, it is practised today at a commercial/industrial level by means of contracts which allow for the supplier to engage in load-shedding (instructing customers to switch off their load at certain times), but such contracts are limited to large commercial consumers and the load shedding clauses are rarely invoked. In the smart grid, the intention is that contracts allowing suppliers, or intermediaries, to alter demand will become far more widespread. The form of such alteration is also envisaged to be less severe – the norm is for incentive-based alteration, rather than automated remote control. The latter, if implemented as a direct control, can be undesirable for ethical reasons, although control with clearly enforced boundaries and retaining the potential for user override can alleviate such concerns (e.g. Boait et al., 2013).

Practical experiments in demand-side response have formed a key component of the Low Carbon Network Fund projects. These projects are industry led, but with strong academic research elements. As yet, results are scarce, but plans show crucial roles for distributed generation and smart management (Gan et al., 2011; Openshaw, 2010).

Demand response can occur at many scales, from large scale factories and foundries, through commercial heating and storage at large and small scales, to domestic fridges and freezers. This study focuses on the domestic scale.

4.2.2.1 Domestic demand response in a smart grid

Demand response in the domestic sector specifically has been considered in studies of smart grid scenarios. Studies have usually focused on:

- the implementation of Time of Use tariffs as a method to incentivise demand side response. In essence, these make the electricity expensive when it is undesirable for customers to consume and less expensive when it is desirable for them to do so

- the influence of more frequent / real-time information about consumption.

Reviews have shown that scheme effectiveness can me measured under two criteria – day-on-day reductions and occasional reduction in critical peak demand.

The potential for such participation is seen to be 0-22% for day-on-day reductions and 10-35% for critical peak reductions. However, many of these studies are rather small and it is notable are mostly from the United States of America. This has implications as there are currently large cooling demands in domestic US houses, which can be curtailed with a large effect, whereas in the UK domestic air conditioning is virtually non-existent (Frontier Economics and Sustainability First, 2012). Their have been two large scale UK trials conducted (EDRP and Northern Irish Powershift trials). The design of the EDRP trials in particular make average and potential savings difficult to quantify in one number, however the indicative total annual savings induced by providing real time information alone is around 4% (AECOM, 2011).

Although the savings potential in the UK seems modest, it should be viewed in the context of policy objectives to increase high power load in a domestic setting (electric vehicles and space heating) and introduce more flexible loads. In addition, the key enabling technology (smart meters) are now mandated to be introduced. The incentive to take part in demand side response schemes for the householder is envisaged to become greater under the pressure of increasing energy prices (audit office NAO, 2013).

Given this potential for electricity demand reduction and the policies to introduce smart meters alongside distributed generation, electric vehicles and electrical heating – the next question to be asked is how will humans interact with a smart electricity supply system. Research into this area is presented in the next section.

4.3 Effect of human behaviour on electricity demand

An essential component of any smart grid system is the ability to modulate electricity demand, usually including domestic electricity demand. This section reviews literature to determine which behaviours are most significant in changing domestic demand and the magnitude of change resulting from those behaviours. Unfortunately, electricity demand is not easy for most people to conceptualise. It has been noted to be "doubly invisible" (Burgess and Nye, 2008) in that (1) electricity cannot be physically seen, but (2) neither is the link between the end of quarter bill and the use of electricity very easily visible. This is viewed as a disincentive or demotivator in the context of taking action to change behaviour with respect to adopting new technology or ways to use it. Some researchers have investigated the effect of smart meters and in home displays of energy consumed on removing one layer of such invisibility (Hargreaves et al., 2010) and the energy change resulting.

Some empirical work has been done to measure the amount of consumption displaced (i.e. moved from peak times into times when the overall grid is under less stress). This can be inferred by the combination of a large reduction in peak demand coupled with a minimal change in overall consumption (implying that the demand has been moved, rather than cancelled). To measure this directly, however, is rather difficult. Smart devices to achieve this demand shifting have been proposed and their potential modelled (Boait et al., 2013).

In the UK, the potential for demand reduction solely via the provision of information to the customer has been found to be small. In early studies, the provision of direct information was found to have potential to reduce total electricity consumption by 15% or even 20% (Darby, 2006). Despite the large potential savings, notes of caution were present – Darby for instance notes that in one study, consumption increased when householders were monitoring their consumption daily without further information on how to save energy (Darby, 2006). More recent and larger studies, however, have found more modest reductions. The Energy Demand Research Project (EDRP) conducted a suite of trials providing information and a range of interventions in pursuit of demand reduction. Despite some flaws in experimental design, the results were analysed to gain insight into the amount of reduction achieved (AECOM, 2011). Estimates of changes in consumption achieved by simply providing information to be acted upon by householders have varied. In part, this is due to how the change has been measured. Usually the studies are predicated on the necessity of reduction in demand, so that is what is tested for. Often, the reduction in peak consumption is measured. This is highly dependent on how frequent the reduction requests (peak tariffs) are and the exact tariff structure. Reductions between 0% and 38% are achieved in small scale studies, while large scale studies in the UK have found that this reduction converges at around 2%. Other studies measure the change in total energy consumed over a certain period, finding total annual consumption reductions between 0 and 22%, with the major UK EDRP trial finding indicative reductions of 4% (Frontier Economics and Sustainability First, 2012).

In the US, Faruqui and colleagues have researched the impact of real time feedback on energy demand (Faruqui et al., 2010), the impact of dynamic pricing on demand (Faruqui and George, 2005; Faruqui and Sergici, 2010) and the ethics of imposing dynamic tariffs on consumers (Faruqui, 2012) from an economically inspired point of view. After conducting a meta-analysis of extant results in the US, they conclude that:

- Feedback and dynamic pricing have an effect on peak consumption power.
- Tariffs with Critical Peak Pricing (greater financial punishment introduced less often) produce a greater reduction in peak consumption (Figure 4.1).
- The reduction in peak consumption with the assistance of technology is much greater than the response mediated by humans alone. (Figure 4.1).

Taken as a whole, the combination of the reviewed empirical work shows that simply providing information about electricity use is not enough to effect large changes in the quantity of energy used and achieve the operation envisaged in a smart grid. Estimates vary from almost no change to 15% in the best case. Peak demand reductions are more significant – particularly in the face of highly punitive tariffs – however sustained large reductions are not seen without technological assistance.

Faruqui finds that the provision of technology to assist in demand management increased the amount of saving potential. This leads to the conclusion that the adoption of technology to assist householders to respond to real time information will be crucial to the development of a smart grid. In addition – adoption of generation technology could offset large amounts of demand and storage technology (whether purchased directly as storage or as a by-product of electric vehicles or heating) could provide the potential to defer demand. This leads to the conclusion that focus on changing repeated behaviour is likely to have lesser quantitative effect than on-off behaviour such as technology adoption.

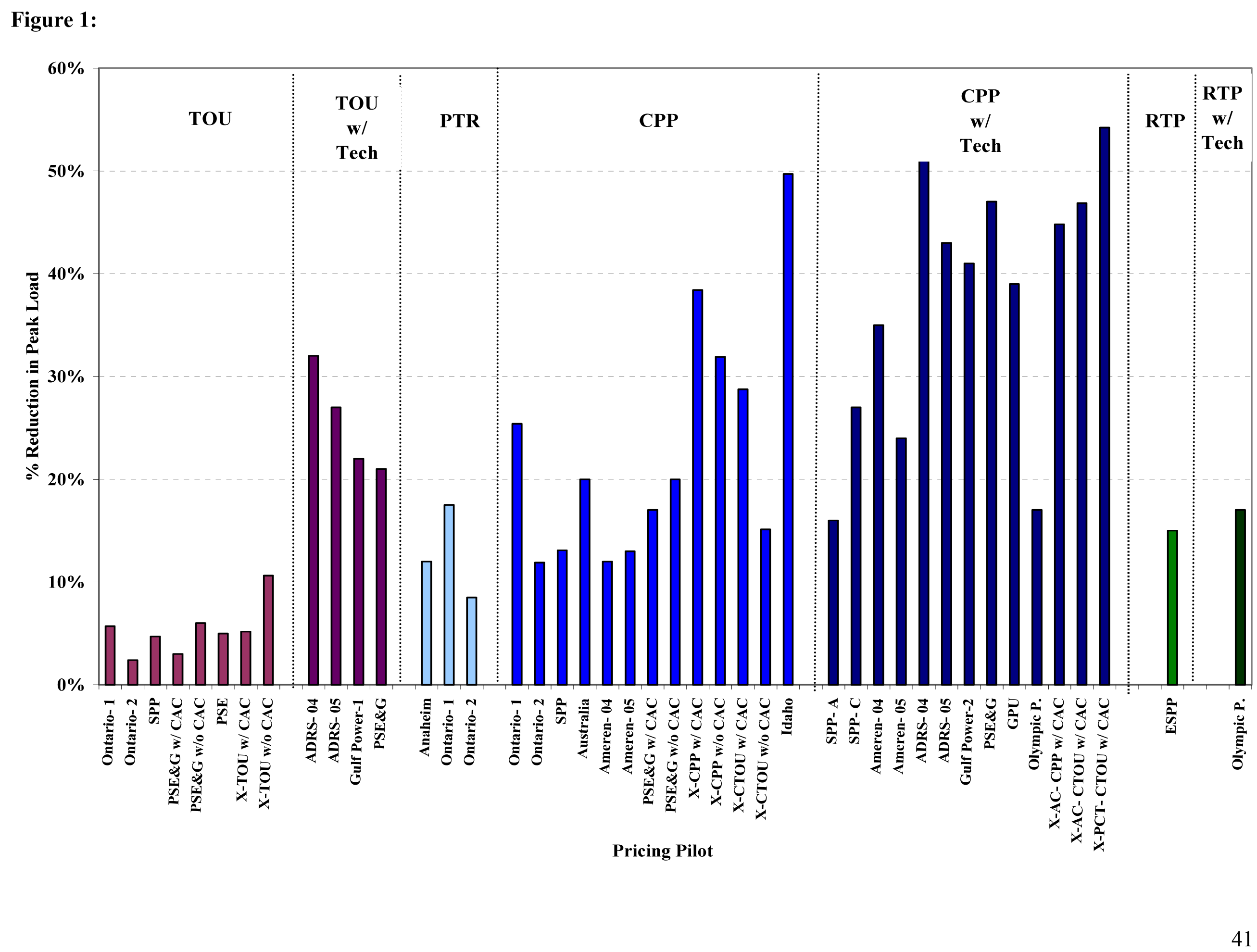


Figure 4.1: Reduction in peak load due to dynamic pricing. TOU indicates Time of Use - a price which varies every day with time of consumption. PTR is a peak time rebate – where customers get a rebate for consumption they avoid at peak time, CPP is critical Peak Pricing, where the price of electricity rises many fold at highly critical times. RTP is real time pricing - of the type often suggested when discussing the smart grid.

Source: (Faruqui and Sergici, 2010)

4.3.1 Repeated behaviour vs one-off behaviour

Research into energy-related behaviour has usually been in the context of energy conservation, given the overriding context of global climate change mitigation. Within this work, conservation behaviour has generally been split into:

1. repeated, habitual behaviour adjusting or curtailing consumption (ongoing, repeated altered behaviour).

2. purchase-related, technology choice or adoption behaviour (one-off, with associated processes and effects).

What is clear from the research reviewed in section 4.2.2 is that the quantitative effect of change of behaviour on a repeated or habitual basis is modest (∼2-4%) even in the presence of near real-time information about consumption (Figure 4.1).

Purchasing and using new electrical equipment will affect a consumer's use profile – possibly significantly. A 4kWp UK solar panel installation will, for instance, potentially provide around 3200-3800 kWh per year (EST, 2015) – around 80-90% of a typical household consumption (DECC, 2015b). While that overall balance might suggest that PV adoption would reduce load on the grid significantly, in fact the grid may see an increase in load as electricity generated when self consumption is not possible (e.g. in the middle of the day for a working household) must be exported, still requiring flow in the grid. This has the effect that PV adoption, in isolation, may not yield as much demand reduction as the total generated would suggest (Glassmire et al., 2012). This effect can be particularly pronounced where PV adoption is clustered and large "reverse" flows may be experienced. The widesperead adoption of PV panels can have a large effect both on the quantity of electricity demanded from the grid and the shape of the demand profile (i.e. the times at which the electricity is demanded). However – in combination with other technologies such as smart controllers and storage (potentially in the form of EVs or heated water), significant grid demand reduction for the household may be possible. This highlights the importance of considering adoption of individual technologies within the context of a smart grid and system transition.

The literature suggests that the effect of adoption has a greater lasting quantitative impact on domestic demand profiles than purely repeated human behaviour change (*pace* Nye et al. (2010)), even when the householder has access to enhanced, near real-time information about their consumption. Faruqui and Sergici (2010) found that where user behaviour did have significant impact, it was greatest when combined with technology (Figure 4.1). There has been some evidence that the purchase of micro-generation devices influences householders to also partake in repeated energy saving behaviours (Bergman, 2009), which serves only to reinforce the importance of technology adoption in user participation within the smart grid. However, the two modes of consumption profile change do not exist in total isolation from each other. Change of habitual electricity consumption must be viewed in the context of other environmental actions, including purchase related behaviours (Barr et al., 2005). Barr et al acknowledge the two different types of householder behaviour and challenge the idea that these should be seen in isolation. Taken in combination, the relative effect of pure behaviour change versus technology adoption support the case for modelling technology adoption as a crucial component of transition to a smart grid, albeit with the acknowledged need to include behavioural characteristics in such a model.

Having reviewed views of the smart grid, research into the transition toward it and the potential influence of human behaviour within it, it can be seen that technology adoption is crucial to domestic participation in and smart grid future.

4.3.2 Studies of low-carbon technology adoption

The adoption of distributed generation can occur across scales (Carley and Andrews, 2012) and has been identified as a key component of change to the traditional hierarchical regime of electricity supply. (Carley, 2009). Rao and Kishore (2010) review models of innovation diffusion with particular reference to low carbon technologies in the form of renewable generators.

The importance of diffusion in the context of a low-carbon transition is acknowledged and examined, with a particular emphasis on the global nature of such diffusion, in a recent special issue of Environmental Innovation and Societal Transitions dedicated to the subject (Rennings, 2014). The focus is on a different theoretical perspective on global diffusion (the Lead Market theory), however the MLP is cited as a useful framework within which to analyse such diffusion (Quitzow et al., 2014; Walz and Köhler, 2014).

It is notable that research into adoption has, in the main, focussed on empirical work. Data from empirical studies has been used to inform the model design and evaluate its performance. Although researching water saving environmental innovation, rather than low-Carbon electrical, Schwarz and Ernst (2009) highlight the lack of diffusion models explicitly considering diffusion of environmental innovations among individuals – noting the exception of Janssen and Jager (31st march 1999) who use a social-psychological formulation for consumer decision making similar to the method used in this study. Schwarz and Ernst (2009) further note that empirical research regarding environmental innovations mostly focuses on energy consumption (e.g. solar energy) and uses both Theory of Planned Behavior of social psychology and lifestyles.

It is clear from studies to date that factors beyond rational economic decision making are extremely important in the process of households adopting renewable technology. In modelling work, the "fashion effect" (adoption imitating local adoptions) has been found to be important (Hamilton et al., 2009). Empirical social studies have investigated the barriers and drivers to diffusion, finding low awareness of the technology alongside unwillingness or inability to pay capital costs (potential lack of access to capital, via savings or loans), lack of understanding and long payback periods to be barriers (Consumer Focus, 2012), whilst measures to help with cost of installation (Consumer Focus, 2012), contribution to a better natural environment, independence from supplier (Jager, 2006) and demonstrating environmental commitment (Balcombe et al., 2015) have all been found to be drivers for installation. It should be noted that lack of access to capital as a barrier means that the wealth of agents is important, rather than considering economic factors as purely relating to payback (with the implicit assumption that capital can be found, for instance via loans, where payback is sufficient). This is discussed further in section 7.4, as household wealth is a parameter that appears to be important to the adoption process, but it is not easy to gather direct data on wealth of households.

It is clear that factors other than the rational economic are important in this decision, which in turn affects the type of adoption models that are needed to understand response to policy. These factors are effectively "rolled up" into the parameters of an S-curve model. If such a model is found not to adequately describe adoption of a given product (as in the case of PV diffusion under the FiT incentive), it is likely that the individual factors affecting diffusion should be examined in a disaggregated fashion.

4.4 Summary

The volume of recent literature reviewed in this chapter demonstrates the active research interest in the transition of the energy system to a low-carbon system and, within that, potential transition of the electricity network to a smart grid (Hammond and Pearson, 2013). There are active calls for models to offer insight in addressing challenges to the the electricity sector in the 21st century, particularly the potential for transition (Pfenninger et al., 2014). To date, smart grid research has focused on definition of future scenarios, however Steward warns researchers that *"The transition to a low-carbon society and green economy must avoid the risk of slipping into a narrative of a destination rather the specific routes toward it."* (Steward, 2012). To this end, the present study is directed toward understanding policy goals in terms of the routes toward smart grid that they are intended to promote and to modelling for insight into those pathways.

The domestic actor has been cited as an important constituent of the transition to smart grid (Verbong et al., 2013), but consideration of the individual actor within the electricity system undergoing transition has been lacking (Hughes and Strachan, 2010). Repeated studies have shown that purely manual participation in the smart grid, even in the presence of enhanced information and dynamic pricing will produce relatively modest opportunities for demand-side management (section 4.2.2). On the other hand, adoption of new low-carbon technology (including microgeneration) will cause much larger quantitative change in consumption – Electric vehicles and heating will introduce much larger loads (Winser, 2010; Pudjianto et al., 2013) microgenerators will introduce a significant, but inflexibly timed, curtailment of load (e.g Balcombe et al., 2015; National Grid, 2012); and smart controllers with dynamic tariffs introduce the possibility of moving those in time (Boait et al., 2013; Faruqui and Sergici, 2010). The literature shows that when considering domestic energy use, the effect of change in the pattern of appliance use is rather less significant than the effect of adoption of new technology (for example, distributed generation, smart controllers or electrical vehicles)

Traditional aggregate models of innovation diffusion, applicable at large scale in many sectors, produce S-curves of adoption emerging from the interaction of heterogeneous members of an adopter population - but not modelling those interactions or the heterogeneity explicitly. These models have been shown to have some weaknesses when describing adoption in a CAS (Rogers et al., 2005). In the electricity sector, modelling of policy impact and future scenarios has focused on large scale economic modelling or scenario building exercises. Such models are limited by their inability to account for non-economic factors, bounded rationality (lack of complete information to the individual) and heterogeneity within the population Kiesling et al. (2012). It is clear from the literature that factors beyond rational economic decision making are important in the adoption of the class of technology under consideration in this work.

There is a lack of research in the gap between developing smart technology devices and envisioning large scale smart grid scenarios, particularly with regard to how the technology will be adopted. This PhD research contributes toward bridging this gap. Agent-based modelling has been shown to be a useful technique to model the interactions and resultant system behaviour within a complex system and to investigate transition. Chapter 5 explores the Agent-based modelling paradigm and previous applications in the sector.

Chapter 5

Agent-based modelling (ABM)

Having proposed the appropriateness of the ABM technique in the description of the theoretical framework adopted (Chapter 2) and the focus of the modelling effort on technology adoption behaviour (Chapter 4), this chapter contains a review of the ABM technique and its prior use in the fields of technology adoption and the electricity supply system in general. The chapter concludes with a summary of the review and the most recent antecedents of the work undertaken.

5.1 ABM in the electricity sector

In their general review of the state of the art in energy modelling for the 21st Century, Pfenninger et al. (2014) view agent-based models as *"the most important"* example of a model class that addresses the need to model across different scales and deal with complexity when modelling modern and proposed energy systems. They note the challenge to conventional modelling paradigms posed by the need to resolve details in time and space when considering distributed renewable generation and the incentives for it. Studies of microgeneration variability further highlight this need, demonstrating that aggregate yields of domestic PV do not give a full picture of the complexity of resulting demand profile and expected benefits of adoption to either the adopter or the grid (e.g. Glassmire et al., 2012).

Over the past two decades, agent-based modelling has been used to model aspects of the electricity sector. A number of reviews of this activity have been conducted (Sensfuß et al., 2007; Weidlich and Veit, 2008; Zhou et al., 2007), the conclusions of which all point to the fact that the majority of ABM activity in the electricity sector has been directed toward studying wholesale market activity (see, for example Banal-Estañol and Rupérez Micola, 2011, Table 1). Firstly, ABM was notably used by Bower and Bunn (2000) to model the newly liberalised UK wholesale electrical power market and has since been used to study wholesale market characteristics intensively in Australia (Chand et al., 2008), Italy (Rastegar et al., 2009), Germany (Veit et al., 2006) and the US (Sun and Tesfatsion, 2007a).

In addition to the focus on wholesale market interactions, ABMs attempting to represent a larger part of the whole electricity supply system via integration of a power flow technical component have been developed. The two largest examples of this style are the AMES model (Koesrindartoto et al., 2005; Li and Tesfatsion, 2009) and the EMCAS model (North et al., 2003; Veselka et al., 2002) AMES is totally open source, whereas EMCAS is a commercial product. The major use of EMCAS was in the study of the liberalisation of the energy market in Illinois in 2007. Specifically, the study was to identify whether any single agent could exercise "market power". The final report from this application of EMCAS (Cirillo et al., 30th April 2006) shows that the model of the transmission grid itself and the power flow was very detailed. EMCAS uses another proprietary piece of software, PowerWorld, to simulate the electrical grid itself (PowerWorld corporation, 2013). This contrasts with the AMES case studies available which, whilst using capable DC-OPF power flow optimisation software, use a simple idealised transmission system of either 5 or 30 buses (Sun and Tesfatsion, 2007b).

The EMCAS model appears to be the most detailed agent based model yet developed to represent an electricity market in combination with the physical network. In common with most models developed using the ABM paradigm, the EMCAS final report cautions that the model results 'should be viewed as "descriptive" and not as "predictive."' (Cirillo et al., 30th April 2006). It should be noted that the EMCAS model was designed to study the effect of new market rules on the electricity market – the technical system was modelled in detail, but was static at this stage, representing the *status quo*. The EMCAS final report also shows that a large number of simplifying assumptions were made with regard to agent behaviour, for instance consumers had no reaction to price fluctuation.

The AMES model is less detailed than that of EMCAS and is squarely positioned as a tool to analyse economic phenomena within the electricity market, particularly exertion of market power and effects of employing Location Marginal Pricing – where price of electricity is intrinsically linked with local grid usage (congestion). At the time of writing, neither model has been used to model the impact of increased renewable generation, storage and/or distributed generation on the network as a whole, although both have been referenced in regard to the possibility of such research.

Other models have been proposed using an Agent Based approach, such as the PowerACE model (Sensfuß et al., 2008; Sensfuß and Ragwitz, 2008), in Europe and NEMSIM in Australia (Batten and Grozev, 2006; Chand et al., 2008). These models have been used to explicitly model carbon emission in the context of the electricity market, but are generally less developed than EMCAS and AMES. NEMSIM has apparently not been used in academic research since an attempt to commercialise the framework while PowerACE continues to be used in academia (Michaelis et al., 2014, e.g).

Recently, the CASCADE framework has been developed (Rylatt et al., 2013, 2015). The author of this thesis contributed heavily to the development of this framework and the research described in this thesis represents one of its first applications. This framework is a step towards addressing the need (identified by Pfenninger et al. (2014)) for a UK centred framework to go beyond optimisation to representing complex interactions.

Pfenninger et al find that:

"Although work is happening on better understanding social and political constraints and uncertainties in future energy scenarios, and on integrating these as well as behavioral aspects into energy systems models, no UK-specific modeling work has been published in this area."

Source: (Pfenninger et al., 2014)

The work described and model developed in this thesis seeks to remedy this situation (e.g. Snape, 2013; Snape et al., 2015).

More recently, in addition to wholesale market modelling, ABMs have begun to be employed in modelling the electricity supply system at a much more local level. The potential to model demand shifting in time in the presence of price feedback from system load has been demonstrated (Roscoe and Ault, 2010). The problem of instability identified in ABMs modelling such a feedback of system load to domestic consumers in the form of a real time price has been addressed, either by damping the system, or decoupling the price from the incentive signal and introducing a probabilistic response (Boait et al., 2013). ABM has also been used to investigate the detailed electrical engineering questions arising from the proposals for micro grids and smart grids. Exploratory and proof-of-concept models have been produced to simulate the use of electric vehicles as storage, taking into account driver behaviour and network power flows (Acha et al., 2011), and to simulate the effect of managing load in isolated micro-grids (Boait and Snape, 2014).

5.2 Learning and decision-making algorithms in ABM

One of the characteristics of ABM that makes it attractive when modelling socio-technical changes is the potential for the agents within the simulation to adapt over time, or learn. With this capability, the decision that an agent makes, or the action it takes, can be different at different times of the simulation, even given the same context. This is important in a range of ABM applications, but is particularly useful in the context of technology adoption as agents who did not adopt a product early in a simulation may well adopt it at a later point. The classic theories outlined in section 2.5 model this as the likelihood of adoption depending on the overall proportion of the population that has already adopted. This is a useful model, and can be implemented as an ABM, but in the real world, people do not have access to the proportion of the population that have adopted a product. Rather, they have access to limited information and heuristics. Rational decision making in the presence of such limited information has been named Bounded Rationality (Simon, 1955).

ABM is well suited to model bounded rationality – any individual agent does not have access to global simulation variables unless they are explicitly calculated and fed back to the agent. Information available to the agent can be restricted by either the distance to other agents, or a network defining those agents that communicate.

ABM allows the practitioner to model information pertaining to a decision and available to each agent changing over time. It allows individual predispostions and beliefs affecting a decision to be encoded into the agents and the effects of each of these factors to be explored. Crucially, it allows the factors to change over time, such that the computer agent displays a limited form of learning.

Brenner 2006 provides a review of learning mechanisms used in Agent-based models, including a classification, or typology, of such mechanisms (Table 5.1).

Table 5.1: Brenner's classification of learning algorithms employed in Agent-based modelling. Augmented and references added by the present author.

Source: adapted from (Brenner, 2006)

<table>
<tr><th></th><th>Non-concious learning</th><th>Routine learning</th><th>Belief-based learning</th></tr>
<tr><td>Psychology-based models</td><td>- Bush-Mosteller learning (Bush and Mosteller, 1955)
- Parameterised learning automaton
- Q-learning (Watkins and Dayan, 1992)</td><td>- Satisficing
- Melioration
- Roth-Erev learning (Roth and Erev, 1995)
- VID model</td><td>- Stochastic belief learning
- Rule learning</td></tr>
<tr><td>Rationality based models</td><td></td><td></td><td>- Bayesian learning
- Least squares learning</td></tr>
<tr><td>Adaptive models</td><td></td><td>- Learning direction theory</td><td></td></tr>
<tr><td rowspan="2">Belief learning models</td><td></td><td></td><td>- Fictitious play</td></tr>
<tr><td colspan="3">Experience-Weighted Algorithm (EWA) learning (Camerer and Ho, 1999)</td></tr>
<tr><td>Models from AI and biology</td><td>Simulated annealing</td><td>- Evolutionary algorithm
- Replicator dynamics
- Selection-mutation equation</td><td>- Genetic programming
- Classifier systems
- Neural networks</td></tr>
</table>

In the electricity sector ABMs, reinforcement learning algorithms have received attention in models of the wholesale market. The Roth-Erev reinforcement learning formulation (Roth and Erev, 1995) has been modified to remove some mathematical deficiencies of the original formulation and used to investigate Locational Marginal Pricing in the US (Illinois) (Nicolaisen et al., 2001). Q-learning (Watkins and Dayan, 1992) and Marimmon-McGratton reinforcement learning algorithms were used and compared by Guerci, who found that different formulations of reinforcement learning suited different assumptions about market participants. In the case investigated (an electrical power exchange) they concluded Marrimmon-McGratton was suitable for simulating greedy sellers, where Q learning was more suitable for long term profit maximising sellers. (Guerci et al., 2007, 2008a) A later work concluded:

"The three learning algorithms considered differ mainly with respect to the information made available to them. Results pointed out that, irrespective of the behavioral model considered, competitive market outcomes are similar."

Source: (Guerci et al., 2008b)

Notably absent from this discussion of learning algorithms are:

1. Models based on psychological models beyond pure reinforcement.
2. Models including social learning (i.e. learning either directly or vicariously from others).

Thus far, ABMs describing elements of the electricity supply system other than the wholesale market (sometimes with power flow constraints) are relatively less well developed. In particular, consideration of demand side behaviour is largely unexplored. Learning and behavioural algorithms to simulate consumers (rather than wholesale market participants) have been under explored. For individual consumers, often the decision-making algorithm used has implicit learning (for instance uses of the Theory of Planned Behaviour), rather than the formalisations described above. This may be due, in part, to the above algorithms focussing on a repeated game form, where the exact same decision (price and quantity of bid) is repeatedly executed with freedom to change the output variables on a (quasi) continuous scale and rapidly repeating opportunities to learn and converge to an (optimal) equilibrium. In contrast, consumer behaviour, especially the adoption decisions considered in this study are binary, are unlikely to repeated or reversed (certainly in short to medium timescales) and so the learning involved is usually vicarious and involves changing of variables that are precursors to the decision, rather than the output of the decision itself.

The model designed and implemented in this study employs the Social Cognitive Theory as the basis of household agents' decision making. This was chosen because it is rooted in theories of social learning. Literature indicates that this theory has not yet been used as the basis of decision making in ABM, but it is an appropriate model of learning and decision-making where social learning by observation is believed to be an important factor. This modelling decision is explained in detail in section 6.5.2.

In addition, the model explicitly allows for re-evaluation of constructs by the agent. This is absent from a number of psychological models, where the action to be undertaken is deemed to be completely specific in detail and time.

5.3 ABM in technology adoption and innovation diffusion

The potential of ABM for modelling innovation diffusion has been recognised for well over a decade (Bonabeau, 2002; Garcia, 2005). Indeed, Hagerstrand's seminal work on innovation diffusion (Hägerstrand, 1965) has been characterised as an ABM (Bergin, 2012). ABM is particularly suited to the study of innovation diffusion as the natural unit of analysis for the individual adoption decision is the individual, yet we are usually interested in the behaviour of the population as a whole. A number of example models have been provided, with initial focus on network effects (Bonabeau, 2002).

One approach to modelling innovation diffusion in an ABM is to explicitly assign to agents one of Rogers' Diffusion of Innovation theory categories (Innovators, early adopters, early majority, late majority, laggards). This assignment may be done probabilistically – according to well researched percentages of the population that fall in each category (Schramm et al., 2010).

However, in the model developed here (Chapters 6 - 8), agents are specifically not initialised as belonging to any of the classic Rogers classes, rather the characteristics of agents are initialised, individual decision making processes are simulated and the patterns of adoption over time are observed. The S-curve characteristic of Rogers' theory and Bass models is likely to emerge, particularly where agents are configured to be largely homogeneous and have perfect information about their context.

Kiesling et al. (2012) review several studies of diffusion of innovation, noting the number of environmental innovations studied using the method. They find that several applications of ABM to innovation diffusion reveal problems with aggregate models that are addressed by the ABM approach. In particular, they note that Zhang et al. (2011) find that aggregate formulations can be inappropriate for environmental innovations due to slow take-off and diffusion discontinuities.

The latter is particularly relevant to this work (see section 7.2.2). Kiesling et al find that many studies report that ABM is a useful technique for modelling the diffusion of innovation. A large number of diffusion ABMs focus on competitive situations and the likelihood of market domination, investigating reasons for competitive advantage. Diffusion of a single technology type as a whole has received less attention. In the environmental innovation category - alongside specific low carbon electricity innovations (section 5.3.1) environmental innovations in water saving have been modelled in the German context, with results indicating that further diffusion in the case modelled was unlikely (Schwarz and Ernst, 2009).

5.3.1 ABM in adoption of low carbon electrical technology employing learning and decision making algorithms

There are very few studies that fall into this category. Despite the range of agent-based models described in the preceding sections, only a handful look at adoption of low carbon technology in the context of the electricity and still fewer in the context of a transition to the smart grid. EVs have been the most popular low-carbon technology whose adoption has been modelled using ABM (Higgins et al., 2012). In a scenario of competing electric vehicle technologies, a probabilistic discrete choice decision model (Tran, 2012b) is employed and finds that the influence of networks on adoption is significant (Tran, 2012a) and that barriers to EV adoption remain high, with conventionally fuelled vehicles remaining competitive even in a situation where major incentives exist to promote the adoption of alternative fuel vehicles (Tran et al., 2012). This series of papers does, however, find ABM to be a useful method for examining the adoption of electric vehicles.

Tran et al's work does not employ a named learning algorithm. One study does so (Zhang et al., 2011) - using simulated annealing (SA) to represent manufacturers converging on optimal EV design, although the empirical basis for either the reaching of an equilibrium or the use of SA is unclear. In the consumer, however, decision making is based on a number of features of the product in conjunction with weightings that the consumer assign to these features. The weightings are assigned to a heterogeneous population in accordance with empirically derived distributions . This allocation of weightings is a similar strategy to that applied in the model developed as part of the research described in this thesis (Chapter 6).

A series of papers examine the adoption of pellet-based heating in Norway, using a similar formulation to the one pursued in this study, highlighting the importance of including psychological insight into the influence of values on pro-environmental decisions (Sopha and Klöckner, 2011; Sopha et al., 2011). The psychological basis for the decision model was the Theory of Planned Behaviour, in this case augmented with social observation by the modellers to introduce an element of social learning (Sopha et al., 2013). This series of studies also incorporates geographical realism and uses households as the agent level of description. They find deviation from the pure S-curves of adoption that the Rogers / Bass model would predict and hypothesise that this may be due to incorporation of explicit household characteristics rather than a population wide classification into Rogers' five adopter categories (Maya Sopha et al., 2011). They indicate that the method is a useful way to combine empirical work and modelling to inform policy.

ABM has been used more recently to study PV adoption in Japan (Murakami, 2014) and Texas (Robinson et al., 2013), investigating geographical distribution of adoption. In the UK, Hamilton et al. (2009) used an ABM to investigate adoption of renewable technologies, focusing particularly on the importance of local observation, which they termed the "Neighbourhood Effect" (Hamilton et al., 2009; Nuttall et al., 2009). In addition, Zhang and Nuttall (2011, 2007, 2008) report on the diffusion of smart meters (a necessary precursor to a smart grid) in a short series of papers, alongside Zhang's PhD thesis (Zhang, 2011). Their work addresses a particular situation where the technology (in this case a smart meter) is being accepted under conditions of almost enforced adoption. The smart meters are to be rolled out to all households in accordance with legislation (see Chapter 3). The model dealt with the relative benefits of different policy scenarios under those constraints, assessing in terms of speed of adoption, final market share of adoption and adopter switching between suppliers (an indicator of ongoing competition). The modelling performed by this research team is particularly relevant as an antecedent to the research undertaken as a psychological theory (the Theory of Planned Behaviour) is used as a basis for decision making and geography is introduced in one of the pieces of work (Zhang, 2011). They conclude that their model *"supports an argument for a direct integration of social psychological theories and agent-based computational simulation."* and show how the ABM bridges the gap between policy intervention at macro scale and decision making at (relatively) microscopic level, both themes which this work takes forward.

The work described in this section demonstrates that the use of ABM with a decision model based upon psychogical theory is an active area of research, useful to investigate the spatial and temporal patterns of eco-technology adoption and PV in particular. The Theory of Planned Behaviour has often been the basis of the decision model, this work builds upon this work, while taking a novel approach by using Social Cognitive Theory as the basis for decision making. The reasons for using that model in particular are explored in more detail in section 6.5.2.

5.4 Summary

ABM has been used in the electricity sector, with the majority of applications concentrating on wholesale market simulations with some whole systems approaches taking account of the physical network, such as EMCAS, AMES and PowerACE (North et al., 2002; Koesrindartoto et al., 2005; Sensfuß and Genoese, 2006). These systems retain a heavy economics bias. A small number of recent works have used ABM to investigate the potential for smart demand-side management (Boait et al., 2013; Roscoe and Ault, 2010).

There has been relatively little ABM work on human behavioural effects on demand, or the adoption of technology. In particular, the study of low-carbon technology adoption using Agent-based modelling with learning agents has been the subject of relatively little exploration. Wood-pellet heating has been the subject of modelling which is the closest to the modelling in this project, showing that the method provides useful insight into policy and sustainability transitions (Sopha et al., 2013). Photovoltaic adoption has been modelled using agent-based modelling, but without the use of social learning agents (Macal et al., 2011; Robinson et al., 2013). Electric Vehicles (Brown, 2013; Higgins et al., 2012; Tran, 2012a; Tran et al., 2012) and Smart Meters (Zhang and Nuttall, 2011, 2007; Zhang et al., 2013) have received some attention in the UK. These works form the most direct antecedents of this study.

Where modelling of adoption has explicitly considered spatial factors, use of real (as opposed to representative) geography has been lacking within the electricity sector (note that Sopha et al considered wood-pellet heating, rather than electricity related innovations). The interaction between adoption of multiple low carbon technologies within the same population has received very little attention and no literature could be found that studied this using ABMs. Few studies of adoption have included resultant effects on consumption at the granularity studied in this project. Thus, the literature reviewed demonstrates that transition to a smart grid is an active area of research, that adoption of technology is crucial within that transition and that ABMs incorporating learning and decision-making algorithms to represent real-world agents (in contrast to zero intelligence or totally rational models) can provide useful insight into that adoption process.

In light of these findings, the model for this study was developed using the method described in Chapter 6.

Chapter 6

Method: Analysis techniques and model design

Bearing in mind the main aim of the thesis, it was essential that the method of investigation allowed for the assimilation of large amounts of secondary data alongside the potential to model scenarios and study their effects. ABM is suitable for this sort of study for the reasons already set out in sections 2.6 & 5.4. The purpose of computational modelling in this research and the nature of conclusions which may be drawn from it were outlined in the theoretical framing of this work (Section 2.7) and this resulted in an iterative workflow between quantitative work and qualitative analysis (Figure 6.1). In this chapter, the methods used to design and implement that model and interpret its outcomes is described. This study takes an intentionally interdisciplinary approach, using the household as a unit of analysis. The interaction of physical, economic and political is played out at the consumer, in the household. The analysis does not endeavour to reduce the household to either a purely social, financial or technological unit.

The model defined for the household is intentionally rich. As the methodology being followed treats the electricity system as a complex, adaptive socio-technical system, the factors that may affect system behaviour are manifold. The methodological decisions and resulting design are outlined in the sections of this chapter.

6.1 Parsimony, or rich description?

The usual engineering method of producing a model is to reduce the model to the most simple description of the system possible and gradually adding complication only when strictly necessary. This method has been popularly branded "Keep It Simple, Stupid", or KISS and has produced many extremely useful models – even when they may not be completely general. A

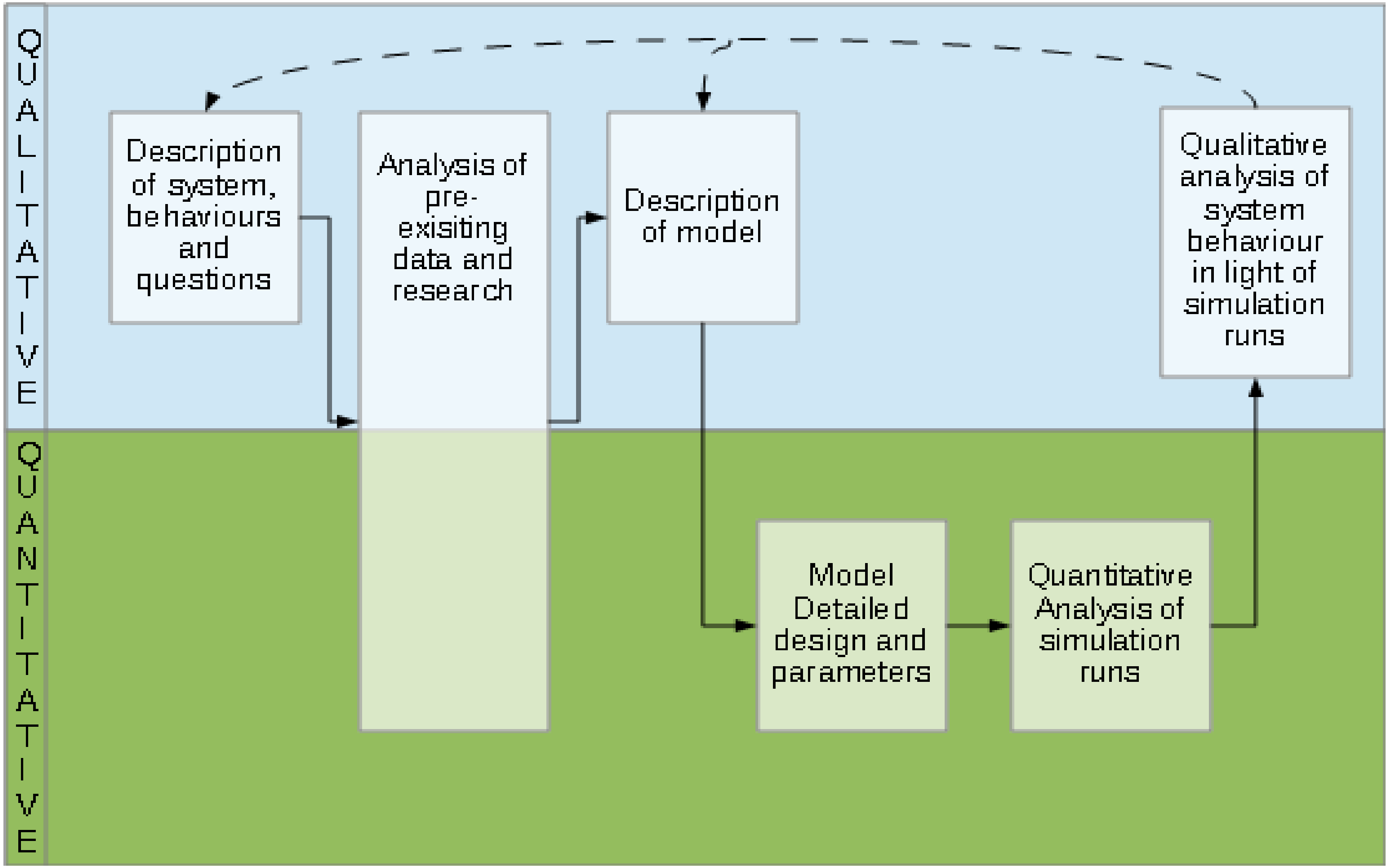


Figure 6.1: Workflow executed in this study, illustrating that the main conclusions to be drawn from an analysis of quantitative model results are qualitative in nature

good, if over-used, example of a model which turns out to be a simplification of a general case but which remains useful is Newtonian mechanics. This reduced, simplified model allows us to describe most moving objects we observe on earth and to design and manufacture extremely complicated machines and mechanisms with confidence. We now know that to describe bodies moving at sizeable fractions of the speed of light, Einstein's relativity model is needed, but this includes Newtonian physics as a subset in the range of conditions most people ever encounter. So, the simple Newtonian model is useful and sufficient in most circumstances. Obviously, Newton did not design his theories as a knowing simplification of a more complicated generality, but it nonetheless illustrates the point that simple models can be very useful.

There is some resistance to slavish adherence to the KISS approach from researchers employing computational modelling in the social sciences and on social and socio-technical systems. An alternative approach (Keep It Descriptive Stupid, or KIDS) has been proposed (Edmonds and Moss, 2005). This approach attempts to describe the system under consideration in the richest fashion possible, taking into account all available information about it – almost the reverse of the KISS approach. It deliberately simplifies a model only when there is good evidence to justify that simplification. KIDS is proposed as particularly suitable where complex phenomena are evident and computational power available. As argued in section 2.2, the electrical supply system exhibits such characteristics and as such is amenable to being modelled using the KIDS approach.

As Edmonds argues in a development of this idea, simplicity is not, in itself, an indicator of "truth" (Edmonds, 2007). Although simplification is used in some parts of the model used in this research, simplicity itself is not used to justify the veracity of the models and, where complex and rich encoding is necessary to describe the system, that is employed. As Edmonds and Moss note, *"Neither the KISS nor the KIDS approach will always be the best one, and complex mixtures of the two will be frequently appropriate"*. Such a mix is employed in the model described here.

6.2 FiT data analysis

The data on adoption of renewable microgeneration under the FiT is available to the public. Data describing all installations prior to June 2013 were analysed in order to characterise the patterns of adoption observed and to provide insight into relevant parameters and their values for the ABM (see Chapter 7 for details). Statistical techniques employed included

- importing the FiT database and census statistics into an SQL database to allow useful interrogation.
- calculation of descriptive statistics for the FiT database and categories of interest.
- analysing adoption over time by means of creating a time series of adoption.
- developing a GIS system to calculate and visualise adoptions per sub-area of the country
- standard regression techniques to look for correlation between some candidate aggregate variables (e.g. population density, indices of multiple deprivation) and observed adoption.
- designing a quantitative method to determine an appropriate spatial scale for modelling (making use of ordinal pattern analysis - see section 7.7 for details)

6.3 ABM method

ABM development requires that consideration is given to what constitutes an agent in the model, how the context in which the agents operate is represented, the appropriate temporal and spatial scales for modelling and the algorithms governing how agents change their state and interact with other agents. The methods used to fulfil all of these requirements are detailed in the following sections

6.3.1 Agency – what is an agent?

The nature of agency is far from a settled issue. The definition of agency for computer scientists talking about Multi-agent systems (MAS)[1] will typically be quite different from the definition of agency for a sociologist discussing the role of agents within society. One example of a MAS definition of an agent is:

*"An **agent** is a computer system that is **situated** in some **environment**, and that is capable of **autonomous action** in this environment in order to meet its design objectives."*

Source: Wooldridge (2008, p. xi).

[1] Multi-agent systems (MAS) are a similar, although not quite synonymous with, Agent-based models or simulations. They use the same software building blocks – software agents encoded with specific behavioural models, but used in a variety of contexts and with (usually) stochastic conditions and interactions. However, the MAS usually forms a system which is designed to accomplish a specific task, whereas the ABM must model a system, rather than *be* one.

It is less easy to find such a concise definition from sociology[2], but Giddens, for instance, in a section defining agency within his structuration theory says:

"Actors not only monitor continuously the flow of their activities and expect others to do the same, for their own; they also routinely monitor aspects, social and physical, of the contexts in which they move"

Source: Giddens (1984, p. 5)

This definition itself would be contested by other sociology scholars, for instance Latour would assign agency to both human and non-human actors (e.g. Latour, 1987, 1992); the debate continues. The different notions of what constitutes agency and, thereby, an agent presents a dilemma in multi-disciplinary work such as this study. Within the ABM research community, definition of an agent tends to be somewhat heterogeneous, apparently often governed by pragmatism.

For this ABM, agent will be taken to mean:

> *A software representation of any real-world entity that can react to the state of the system as it observes it and change its behaviour accordingly.*

This is quite a wide definition of agent – it is purposely formulated to allow for the encoding of automatic devices alongside humans and corporate agents, such as firms. In an ABM concerned with the electricity supply system as it transitions to a smart grid, it is likely that all three of these agent types will have significant roles in the behaviour of that system. Whilst the main agent under consideration in this work is the household, it is important to retain the flexibility to encode other types of agent if the model is to have the capability to reflect the effects of household behaviour on the system as a whole.

6.4 The CASCADE framework

As noted in the introduction, this research was undertaken within the CASCADE project[3] (Rylatt et al., 2013, 2015). As such, large parts of the CASCADE electricity supply system ABM framework were developed by the author of this thesis. In the interests of clarity, where part of the CASCADE framework not developed by the author was used in the course of this study, it is clearly refer-

[2]One might argue that a concise definition of agency is not the point of a sociological investigation of its nature

[3]CASCADE was an EPSRC funded project specifically to develop a smart grid ABM framework - grant number EP/G059969/1 `http://http://gow.epsrc.ac.uk/NGBOViewGrant.aspx?GrantRef=EP/G059969/1`. The framework was subsequently developed under the AMEN project - again funded by the EPSRC under grant number EP/K033492/1 `http://gow.epsrc.ac.uk/NGBOViewGrant.aspx?GrantRef=EP/K033492/1`.

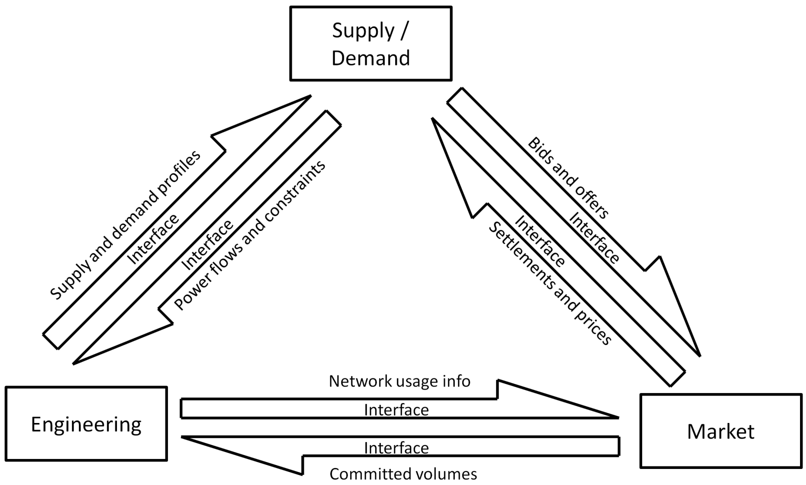
enced to a paper by the author of that piece of code. All code for the adoption model and the household physical model was developed by the author. Authorship of each line of code in the CASCADE framework is recorded by the software version control system where the framework is published as open source code (at `http://github.com/rsnape/CASCADE`).

6.4.1 CASCADE ontology

The CASCADE framework characterises the grid as three interacting systems, the wholesale market, the physical network infrastructure and the supply and demand required by users of the grid. The concept of ***Prosumer*** agents and ***Aggregator*** agents is used to characterise the generic features of, respectively, agents which have a physical grid connection (e.g. households, factories, offices, power stations) and those which act on behalf of such agents in the wholesale market (e.g. utility companies, industrial power purchasers, power station owners). The term prosumer (after Toffler, 1981) has become common in literature describing future electricity supply systems, used to describe an agent which may produce or consume electricity. At either end of the spectrum, a prosumer may be a pure generator (for instance today's power stations), or a pure consumer (such as most households today). However, the prosumer abstraction allows for a rich heterogeneity of agents (like a household with microgeneration, or a community level storage facility) who may produce, consume and store electricity.

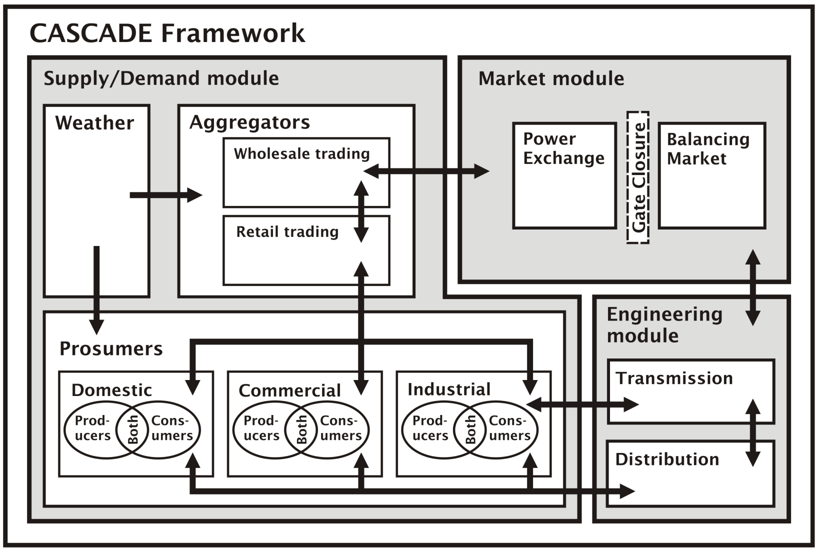
The ontology used to describe the electricity system is most easily described in two layers. In one layer the three modules interact by passing information between each other at each timestep (Figure 6.2). The research described in this thesis utilises the supply demand module of the CASCADE framework (see figure 6.2a); the Household agents developed are domestic prosumers, which are conceptually located within the box at the bottom left of figure 6.2b.

At the same time, the entire framework is based on the behaviour and interaction of the prosumer and aggregator agents. Each module of the framework will query different variables within the agents at each timestep and then send different information to them. For instance, the economic module would handle a market settlement agent querying an aggregator for its `net_demand` and `price` variables and send back a `clearing_price`. The physical module would query `net_demand` for each prosumer and return `voltage` and `frequency`. In this study, we utilise the behavioural module, named the Supply/Demand module, which executes behavioural algorithms in the agent and monitors output decisions. The other modules still run in the simulation



(a) The dataflows between modules in the CASCADE framework

Source: Rylatt et al. (2015)



(b) The components of the CASCADE framework and relations between them

Source: Rylatt et al. (2013)

Figure 6.2: The three interacting modules within the CASCADE framework

and we can utilise their output (for instance using the physical module to measure total demand across the population of agents), but the primary interest is in the supply/demand module.

A typical model agent population consists of one or more aggregators, each hierarchically linked to thousands of prosumers. The prosumers may be linked by a network representing the physical electricity grid, while in the case of more than one aggregator they can be linked by a network representing economic or market links. The framework does not impose constraints on how many agents or networks may be added to a model, although execution time imposes practical limits.

The detailed features of the CASCADE framework and its characterisation of the electricity supply and demand system are documented elsewhere (Rylatt et al., 2013, 2015). The use of the term prosumer is to highlight the fact that as the electricity supply system makes the transition from its current state to a smart grid, more and more erstwhile consumers will become both producers and consumers of electricity – as is demonstrated by the adoption of PV on domestic buildings.

6.5 The adoption model

The adoption model is configured as shown in Figure 6.3. It utilises some of the generic capabilities of the CASCADE framework to automatically assign standard features to households (such as the building physical model for a household and weather file handling) in order that demand profiles can be generated to facilitate the calculation of expected benefit to the household as part of the adoption decision model. However the adoption model itself and decision algorithm (sections 6.5 – 6.7) was developed specifically for the research described in this thesis.

Of course there will be many thousands of households, rather than the illustrative 10 in figure 6.3. Each household agent holds a number of parameters described in the following sections. These parameters are varied for the experimental work and results presented in chapter 8.

6.5.1 The Household agent

As mentioned in the chapter introduction, the household is the fundamental unit of analysis in this study, chosen for three reasons:

1. the existing data on technology adoption contains separate data points per household;

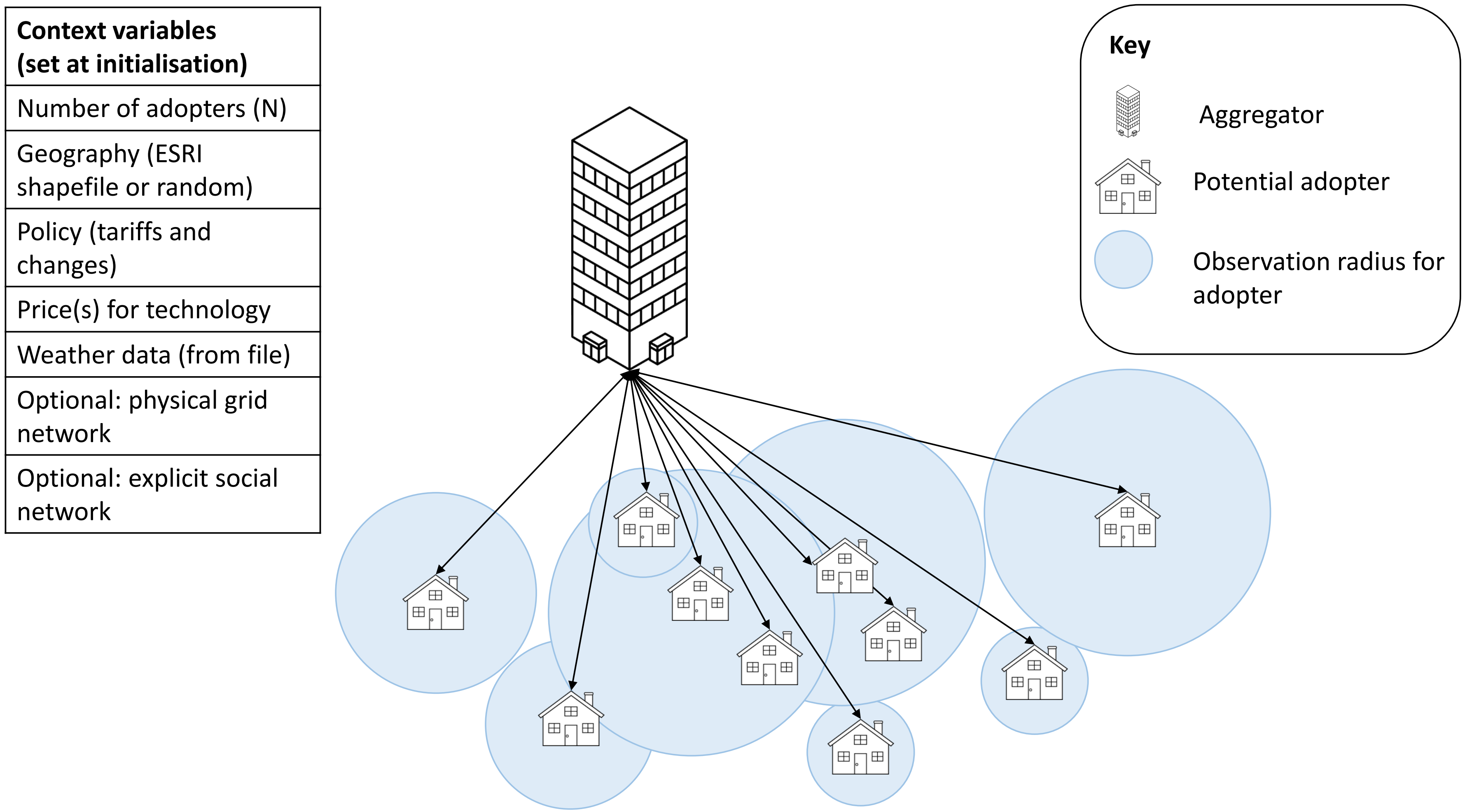


Figure 6.3: A conceptual diagram of the adoption model. All household agents have an economic tie to an aggregator agent, which collates net demand. In addition they have access to context veriables such as tariffs, material costs and weather. The agents can interact by observation of other agents within a certain radius

2. existing data and models usually deal with the household as the lowest level unit. For example, models to generate consumption patterns usually give consumption profiles per household. Although some models exist which give consumption patterns at lower resolution (e.g. per appliance), these are often aggregated to a per household profile for model output and are usually only claimed to be useful at the per household level;

3. the household is the point in the system where the different factors affecting consumption most logically combine. When using the household as the unit of analysis and including householder behaviour alongside technical characteristics for the household, models from a number of disciplines may be employed.

The decision to use the household as the modelled agent can be considered in contrast to using occupants as the agents. It imposes a potential limitation in the lack of ability to capture the effects (if any) of intra-household dynamics on behaviour. However, for adoption behaviour this does not appear to be significant. In most cases, appliances and artefacts adopted (PV in this case, but also washing machines, heat pumps etc.) are adopted per-household, rather than per-individual. The high level overview of the properties of the adopter agent is given in Figure 6.4, with the detail of the specific psychological model used given in section 6.5.2 followed by detail of the PV specific model in section 6.7.

6.5.2 Psychological models within household agents

Unfortunately, households do not lend themselves to intuitive description as having agency. They are, generally, a collection of individuals, all of whom will have a greater or lesser influence on household decisions, all living with various physical artefacts. In modern households, the individuals within them may own various electricity consuming devices and the patterns of consumption for those devices will be dependent on that individual's lifestyle, needs and desires. This could be levelled as problematic given the decision to model at the household level.

However, in this study we are concerned with the decision to adopt infrastructural technology, such as PV systems, or smart home controllers. In the case of electricity usage decisions, there is some evidence to suggest that decisions are most usually taken by a powerful dyad within the household (for instance, the parents in a single family household) or a powerful individual (Thøgersen and Grønhøj, 2010). Theories of behaviour from psychology (e.g. those compared

Household (Adopter agent)

Characteristic variables set at initialisation	Name	Value
Initial propensity to adopt	microgenPropensity	Per DEFRA category
Available capital	PVCapital	50000
Position	Lat,long	Per shapefile
Observation radius	observedRadius	Per experiment
Initial demand profile	netDemand	standard CASCADE model (per agent)
Physical characteristics	potentialPVCapacity	2-4 or 0 if unsuitable
Psychological model weights	W_{i-j}	Per experiment
Tech ownership	hasPV	--

Decision making algorithm

SCT algorithm

Figure 6.4: Member variables for the Household adopter agents

in Table 6.1) describe the behaviour of an individual. This presents a problem when applying them to a model of domestic electricity consumption, where data are monitored at a household level. Work has been conducted (e.g. Thøgersen and Grønhøj (2010) in Denmark) which has explicitly considered this issue and analysed electricity consumption and energy saving behaviours with the unit of analysis being the household whilst gaining empirical evidence of the influence of intra-household factors on the behaviour. They found a high level of correlation between survey respondents (usually spouses) within the same household. This suggests that a reasonable modelling approach is to use a model from psychology as the main model of decision making within the household, albeit with a caveat that acknowledges the abstraction of a potentially multi-person decision to a single person model. As will be shown later, this simplification does not appear to substantially affect the ability of the model to describe various patterns of adoption, including those observed in the UK for PV installations.

The decision to model household decision making based upon an established psychological theory having been made, the specific psychological theory used to represent behaviour in the agents was selected. A number of psychological theories providing models of human behaviour around decision making and behaviour change were reviewed (Table 6.1). The table is not intended to be an exhaustive review of all theories of behaviour change (see, for example, Jackson (2005) for a comprehensive review of behaviour theories with respect to pro-environmental behaviour). The selections in Table 6.1 are chosen to illustrate the variety of approaches available, their similarities and differences and the implications which each may have if their constructs are used to represent behaviour change in a computational model.

Table 6.1: Comparison of behaviour change theories

Theory	**Constructs**	**Author**	**Generic / Specific behaviours**	**Linear / recursive**	**Notes on use in ABM behavioural representation and pro-environmental context**
Theory of Planned Behaviour (TPB)	• Attitude • Subjective Norm • Perceived Behavioural Control • Intention	Ajzen (1991)	Specific	Linear	Well supported applicability and relative influence of constructs in various contexts via extensive meta-analyses. Extensively used in the pro-environmental behaviour context. Theory of Reasoned Action is the antecedent.
Theory of Interpersonal Behaviour (TIB)	• Attitude • Social Factors • Affect • Intention • Habit • Facilitating Conditions	Triandis (1977)	Specific	Linear	Explicit consideration of habit important in describing repetitive behaviours. Greater complexity of the model – increases difficulty of encoding and potential to introduce hidden assumptions when coding.
Belief-Desire-Intention (BDI)	• Beliefs • Desires • Intentions	Bratman (1987)	Specific	Linear	Well suited to programmatic representation and well used in computational agent based systems. To some degree has become *de facto* standard in ABM (Elsenbroich and Gilbert, 2014). Foundations in philosophy with folk psychology terminology and justification.

Theory	Constructs	Author	Generic / Specific behaviours	Linear / recursive	Notes on use in ABM behavioural representation and pro-environmental context
Value-Belief-Norm (VBN)	• Values • Beliefs • Personal Norm	Stern (2000)	Generic	Linear	Integrative theory drawing on the New Environmental Paradigm (Dunlap and Van Liere, 1978) and Norm Activation Theory (Schwartz, 1973). The constructed personal norm may be used as a basis on which a range of pro-environmental behaviours are enacted. This is attractive in terms of reduction of programmatic complexity.
Social Cognitive Theory (SCT)	• Expectation • Perception of others • Self efficacy • Goals • Outcomes • Socio-structural factors	Bandura (1986)	Specific	Recursive	Able to incorporate social influence, feedback from historical experience and internal influencers. Has been applied to the diffusion of technology innovations. Habit not explicitly accounted for.

6.5.2.1 Selection of Social Cognitive Theory as the pyschological model

The final decision to use Social Cognitive Theory (SCT) was taken as it had the following characteristics:

1. It was designed to use ideas of reciprocal determinism – i.e the interaction and interde-

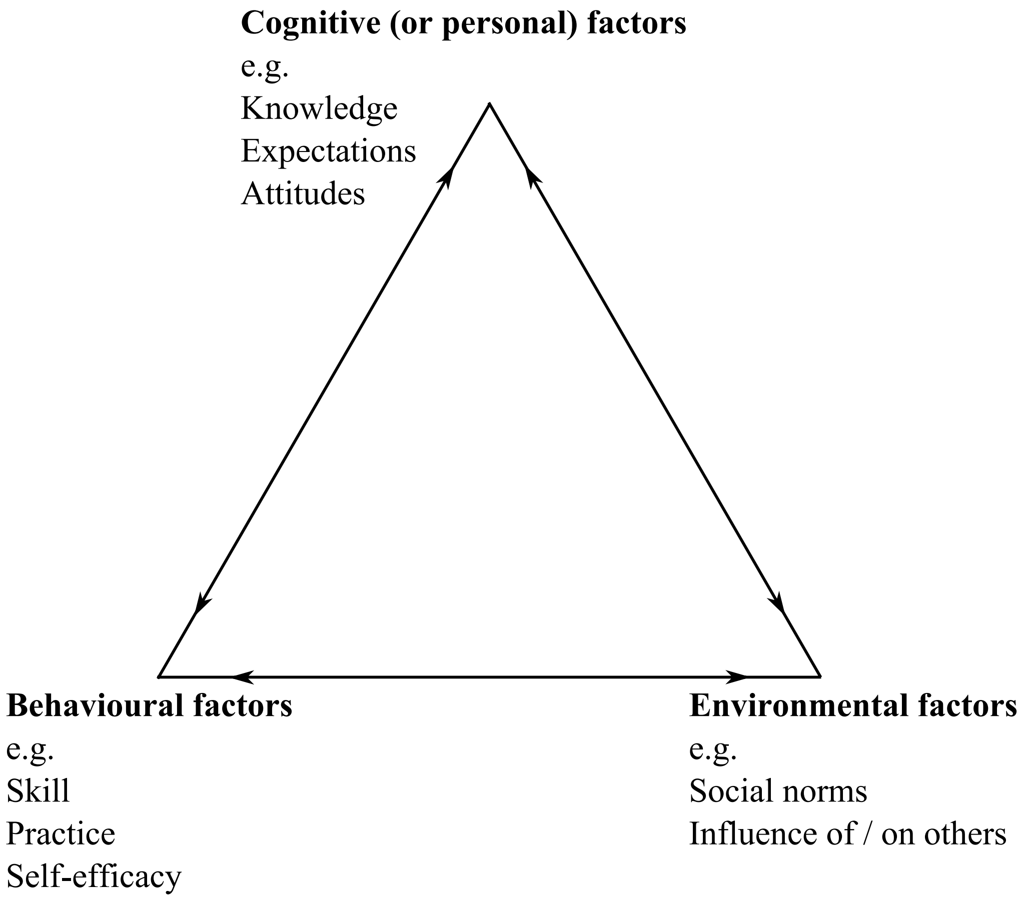


Figure 6.5: Social learning theory, highlighting reciprocal determinism between individual behaviour, society and environment. After Bandura (1977, 1989).

pendence of the person, context (environment in his terms) and behaviour. e.g. (Bandura, 2001)

2. It explicitly considers repeated evaluation of constructs

3. It explicitly combines social factors with those endogenous to the person and structural factors

4. Social learning is central to the theory and the role of agency within social learning is elaborated (Bandura, 2001).

In developing the SCT, Bandura drew on his earlier work on social learning theory, which focused on the reciprocity described in 1 above; this is often illustrated as a closed triangle where all three factors mutually influence (Figure 6.5).

He also placed emphasis on self-efficacy, a construct introduced in an effort to unite two trends in research into behavioural change: theory holding that cognitive processes were responsible for behaviour change alongside the practical observation that performance based procedures most often successfully changed behaviour (Bandura, 1977). The thrust of the idea is that a person's perception of their own ability to enact a behaviour which may achieve their goal is a major driver of whether they perform that behaviour. This perception of self-efficacy is influenced by a number of factors including the person's own past success (i.e. reinforcement), vicarious observation of others and environmental factors.

The combination of reciprocal determinism, self-efficacy and social learning resulted in the elaborated SCT model (Figure 6.6)

Other psychological models have been deployed as, or served as inspiration for, models of agent behaviour in ABM. Within the electricity sector, the TPB (Nuttall et al., 2009; Zhang and Nuttall, 2011, 2007) has been used in this way, whilst Elsenbroich and Gilbert (2014) argue that *"The standard agent architecture of agent-based modelling is the Belief-Desire-Intention (BDI) agent"*, although most models described in the literature augment the architecture in some way. However, neither BDI or TPB have the combination of features described above that makes SCT particularly suitable for modelling gradual change in agents over time leading to technology adoption and observation of the overall effects of that on the system.

Use of SCT as the underlying model of behaviour in an ABM is a novel application of the theory; SCT would more usually be used in an empirical study to interpret primary data gathered from experiment participants (as has been done, for example, within the domain of pro-environmental behaviour by Thøgersen and Grønhøj (2010)). The modelling employed in this thesis uses the theory as a basis for a model of decision making and is not to be taken as an empirical psychology study. Results from studies using SCT have been used to inform the model design when mapping theory to variables and deciding values of parameters determining relative strengths of constructs and relationships.

6.5.3 Social modelling within agents: perception of others

In the ABM developed, household agents interact socially by observation of the actions of other households. This mode of interaction was chosen in preference to a model of direct interaction (e.g. one-to-one agent communications of their internal variables) as the installation of devices

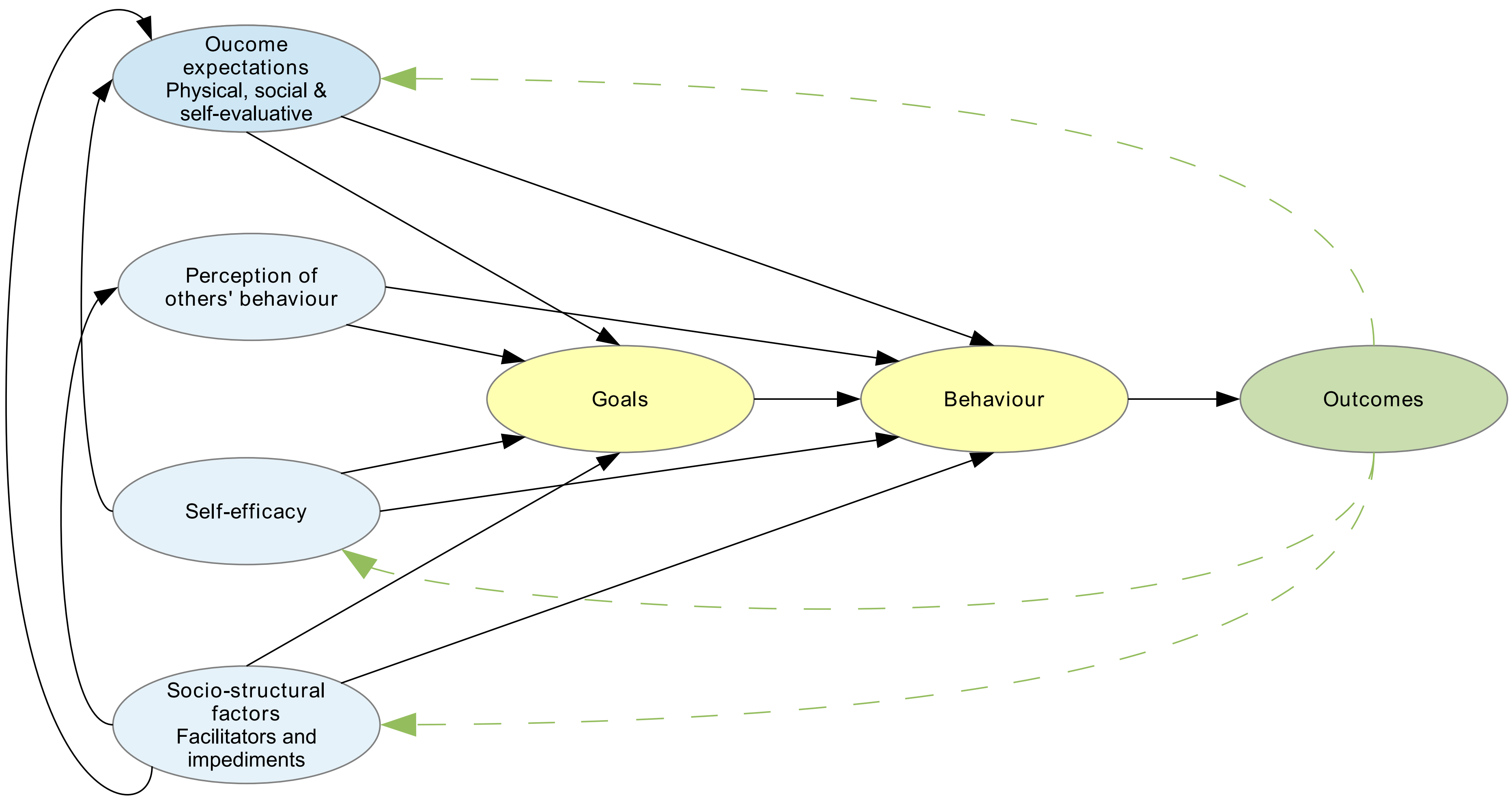


Figure 6.6: The SCT model. Constructs combine to influence a person's goal setting and behaviour. In turn a behaviour results in an outcome, which itself influences the original constructs (shown here in green).

Source: (after Bandura, 1986)

under consideration in the study would be far more widely observed than directly discussed. It was also noted during literature review that several standard constructions of a simulated social network to mimic the interactions in an ABM can prove to be unsatisfactory when compared with real world social networks (Hamill and Gilbert, 2009). Thus, simulation of an explicit social network for direct communication between households was not undertaken and vicarious learning via observation based upon geographical proximity was used as the modelled proxy for social interaction. Without a large scale survey to determine true social networks, which would be beyond the scope of this research, the geographical proximity is a reasonable proxy for social interaction rather than a simulated but fictional explicit network. See Snape et al. (2015) for an elaboration of this argument.

6.5.3.1 Influence of social learning

Social learning is a term which describes the process of adapting behaviour in response to influence from social contacts (e.g Wenger, 2000). It intrinsically links learning of new ideas or behaviours (or knowledge and actions) to the social context in which they exist and has been used to describe both SCT (Bandura, 1986) (unsurprisingly, as social learning theory along with the idea of self-efficacy were fundamental precursors to SCT). In their investigation into the sociopsychological drivers of energy-use patterns, Nye et al. (2010) conclude that *"...'social' factors are central to explaining patterns of aggregate electricity demand"* and highlight the need for further exploration in this area. One of the ways in which social factors can influence electricity demand is, of course, via influencing technology adoption and it is investigation of this that forms the major experimental part of this research (sections 8.3.2 – 8.3.2.4)

6.6 SCT algorithm

The household agent combines the constructs of the Social Cognitive Theory in its decision making algorithm. To operationalise this within the ABM, each construct (oval within Figure 6.6) is given a numerical value, and each connection in the model (arrow within Figure 6.6) has a weight, also a numerical value corresponding to the relative influence it has on the decision making process. The SCT model was programmed as follows. Let C be the set of constructs:

$$\begin{aligned}\{\ OE &= \text{value of outcome expectation construct},\\ PO &= \text{value of perception of others' behaviour},\\ SE &= \text{self-efficacy},\\ SSF &= \text{socio-structural factors},\\ G &= \text{goal},\\ B &= \text{behaviour},\\ OUT &= \text{outcome}\ \}\end{aligned}$$

Then

$$\begin{aligned} c_i : i \in C &= \text{construct weight for construct } i\\ w_{i-j} : i, j \in C &= \text{link weight between constructs } i \text{ and } j\end{aligned}$$

Note that where a relationship does not exist in the SCT model (Figure 6.6), this can be represented mathematically by $w_{i-j} = 0$. This technique may also be used where an experimental setup wishes to exclude the influence of one construct on another.

The values are evaluated according to the pseudo-code algorithm 6.1 (a light grey line with ## at the beginning denotes a comment).

Algorithm 6.1 SCT evaluation algorithm

update c_x from external factors ## (e.g. observation of neighbours, financial change)
Calculate feedbacks to update the first level constructs with a weighted sum
$c_x := \dfrac{c_x + \Sigma\,(c_y \cdot w_{x-y})}{1 + \Sigma w_{x-y}} : x \in \{OE, PO, SE, SSF\}, y \in \{OE, PO, SE, SSF, OUT\}$
Update the value of goal construct, similarly with a weighted sum
$c_G := \dfrac{\Sigma\,(c_x \cdot w_{x-G})}{\Sigma w_{x-G}} : x \in \{OE, PO, SE, SSF\}$
Update the value of behaviour construct, similarly with a weighted sum
$c_B := \dfrac{\Sigma\,(c_x \cdot w_{x-B})}{\Sigma w_{x-B}} : x \in \{G, OE, PO, SE, SSF\}$
if $c_B > adoptionThreshold$ **then**
  return adopted
else
  return notAdopted
end if

This algorithm executes every time the decision process is called - values of constructs are retained in the model object until explicitly set to another value (i.e. they are not all set to zero at the start of each algorithm evaluation). The frequency of calling the algorithm is a parameter of specific scenario design. The variables which map to each construct in the first (update) line of the algorithm depend upon the technology being adopted and the specifics of the experiment being run. These details for the PV case are given in section 6.7 (Figure 6.7 in particular).

6.7 PV specific design

6.7.1 Decision making algorithm

The decision making algorithm is triggered at a randomised time for each household, at which point the household runs through algorithm 6.1 and adopts or does not. Figure 6.7 sets out the program flow for this process. The following sections describe the detailed mapping of constructs within the SCT to model variables.

6.7.2 Mapping the SCT to householder agent attributes

The household agent has variables mapped to the SCT constructs as shown in Table 6.2. Each mapping has a subsection describing the rationale and encoding in the model below.

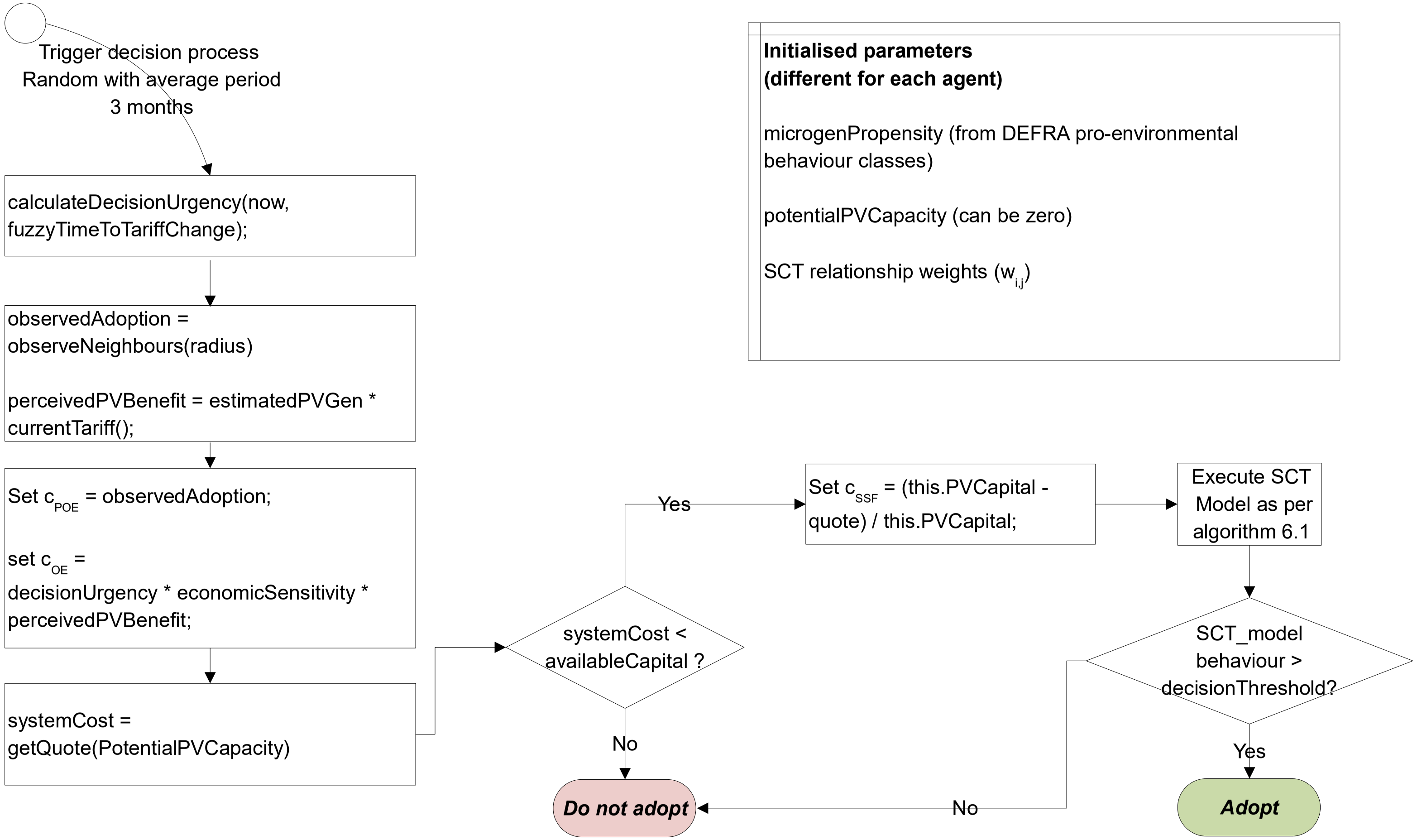


Figure 6.7: High level decision making algorithm program flow

Table 6.2: Mapping SCT constructs to model variables

Construct	Contributing factors	Data basis (where applicable)	Variable(s) in model implementation
Outcome Expectations	Expectation that installing the technology will contribute to avoiding climate change.	DEFRA (2008)	microgenPropensity Based on Pro-environmental behaviour categories.
	Expectation that installing the technology will save money on electricity bill	PV generation based on weather file. Consumption profile based on CASCADE standard models	Expected output given size of system
	Expectation that the investment outlay will quickly be offset by savings on electricity bill (i.e. perception of payback period)	tariff levels, Energy Saving Trust (EST) data on quotes over time, EST data on average output for PV systems (EST, 2012).	Payback period (noisy) calculation by agent of expected monetary benefits (gets quote, works out previous bill and therefore monthly benefit & payback period based on tariff at installation time)

Construct	Contributing factors	Data basis (where applicable)	Variable(s) in model implementation
Perception of others' behaviour	Perception of number of people having solar panels installed	Calculated within model	Fraction of neighbours with PV panels installed
	Perception that people are having solar panels installed because of the money they will be paid for the electricity they generate		
	Perception that people are having solar panels installed because they care about reducing climate change		
Self-efficacy	Internal belief in the ability to have the technology installed	DEFRA (2008)	Based on Pro-environmental behaviour categories.
	Perception of the ease with which others have installed the technology.	–	Not explicitly modelled in this implementation

Construct	Contributing factors	Data basis (where applicable)	Variable(s) in model implementation
Socio-structural factors	Building size (is there enough space to install a viable PV system)	Typical capacities from Ofgem (19th April 2013) see Chapter 7	pvCapacity variable set at model initialisation
	Buiding orientation (is there a roof facing between SE and SW).		pvCapacity set to zero to model unsuitable house orientation
	Tenancy – owner occupier / private rented / social housing etc.	Census data for percentages of each category in target area	For the purposes of this study, non-owner occupiers considered simply "non adopters"
	Household income bracket	Drawn from national income statistics	available capital for PV investment
Goal	Desire to adopt technology (PV)	–	internal construct value within model
Behaviour	Procuring the technology and having it installed.	–	Agents have a threshold based on pro-environmental category. If this is exceeded, the agent will get a price and, if sufficient funds, procure.
Outcomes	Money saved on electricity	calculated by the CASCADE model	Difference between total energy bought from the grid before and after adoption
	Perceived ease of installation	–	Not implemented in this model

6.7.2.1 Outcome expectations (c_{OE})

The outcome expectations for installation of technology are determined as a combination of the following factors

1. Expectation that installing the technology will contribute to avoiding climate change.

2. Expectation that installing the technology will save money on electricity bill

3. Expectation that the investment outlay will quickly be offset by savings on electricity bill (i.e. perception of payback period)

These factors are combined in the ABM decision algorithm as follows. Firstly, each agent is assigned a number characterising their propensity to take action to avoid climate change. The way that this number is determined varies over the suite of experiments undertaken, from a fixed value for all agents to a biased random assignment based on the pro-environmental behaviour categories defined by DEFRA (DEFRA, 2008). This parameter corresponds to expectation 1.

The agent perceives the likely economic savings as follows. The price of photovoltaic cells is part of the context of the simulation. Any agent can request a price to install PV of a given size, this will be returned as the price to buy the PV cell, plus a randomly selected percentage profit and installation cost. In this way, agents will experience heterogeneous installation costs, but the average installation cost will move with the price of the PV equipment. Similarly, they can obtain an expected saving – this will take into account the orientation of their property (the latitude is considered the same for all agents as the modelled geographical area is quite small). This will be as per the EST estimated saving, but will be subject to error. This corresponds to expectation 2 above.

Armed with the above variables, the agent can estimate their perceived payback period as the cost of installation divided by their estimated saving on their bill. This may not, of course, turn out to be accurate. This corresponds to outcome expectation 3 in the list above.

Each agent is assigned an economic sensitivity, which governs the importance, or weight, they give to economic savings (expectations 2. & 3.).

Thus c_{OE} is determined as a dynamic calculation of the economic benefit of installing PV (Figure 6.7) multiplied by the economic sensitivity of the agent (also based on the DEFRA categories as they describe the economic sensitivity for each category) and the decision urgency (calculated within the model - see section 8.3.1 for details of calculation method in the scenarios simulated).

6.7.2.2 Perceptions of others' behaviour (c_{POE})

Households' perception of others' behaviour for the PV system is considered as having the three components:

1. Perception of number of people having solar panels installed
2. Perception that people are having solar panels installed because of the money they will be paid for the electricity they generate
3. Perception that people are having solar panels installed because they care about reducing climate change

It should be noted that component 1 and components 2 & 3 simulate somewhat different mechanisms. The former is entirely vicarious – it is easy to observe a solar panel on someone's roof without having to know them or engage with them in any direct way. The latter two rely on some degree of direct communication where one or more agents communicate their own parameters to the observing agent. Direct communication between agents is not utilised in the experiments presented in Chapter 8, in order to maintain the tractability of interpretation. Thus, perception of others' behaviour is modelled as the observation of others' PV installations within the radius that they observe (set at simulation start). This influence on adoption is similar to the "Fashion Effect" identified by prior research into agent-based models of renewable technology adoption (Hamilton et al., 2009; Nuttall et al., 2009). The value of the perception of others' behaviour construct (c_{POE}) is thus varied by altering the radius within which each agent observes neighbours.

6.7.2.3 Self-efficacy (c_{SE})

Self efficacy is determined as a combination of

1. internal belief in the ability to have the technology installed
2. perception of the ease with which others have installed the technology.

The perception of ease with which others have installed the technology is captured by the observation of number of installations in the neighbourhood as described in 6.7.2.2 and not separately modelled in the experiment conducted for this thesis. The internal belief is determined at simulation initialisation, assigned from a random distribution weighted by the agent's pro-environmental behaviour category (ability to install was one of the measured variables in the DEFRA study to determine pro-environmental behaviour categories and is therefore used here).Thus c_{SE} is determined by the economic ability variable set at initialisation.

6.7.2.4 Socio-structural factors (c_{SSF})

Both structural and social considerations may be perceived impediments or facilitators for technology adoption. Specifically, in this research these are:

1. Building size (is there enough space to install a viable PV system)
2. Building orientation (is there a roof facing between SE and SW).
3. Tenancy – owner occupier / private rented / social housing etc.
4. Household income bracket

These factors are implemented in the model as boolean variables, rather than on a sliding scale of influence as in the previous factors. Thus, if the household size or orientation is not viable, PV adoption cannot take place. Similarly, if the tenancy is not owner occupied – the household agent itself cannot decide to adopt. If the income bracket is too low (taking into account the level of investment required) the technology cannot be adopted.

6.7.2.5 Goal (c_G)

In the context of this study, we are interested in one goal of each agent: to adopt a particular piece of technology (i.e. a PV panel). Note that this is distinct from the behaviour of procuring such a piece of technology and having it installed – other factors can affect this as per Figure 6.6. c_G is an endogenous model construct, which is not determined by any further parameters, but calculated according to algorithm 6.1.

6.7.2.6 Behaviour (c_B)

Procuring the technology and having it installed. This is the action taken by the agent if the other factors combine to mean that the threshold for installation has been reached. c_B is the ultimate result of the combination of factors from the SCT algorithm (6.1), which is then compared with a threshold value to determine whether the technology is adopted. In this study, the threshold is a hard threshold.[4]

6.7.2.7 Outcomes (c_{OUT})

The outcomes represent the evaluation of the behaviour as perceived by the household agent. The feedback from these into the other constructs constitutes a form of reinforcement learning. The outcome is a weighted sum of the following factors, which are calculated from the CASCADE demand model. Thus c_{OUT} is measured as the economic benefit of installation.

The model has been implemented with that capability to include more factors in the c_{OUT} construct, such as the ease of installation or perceived functioning of the technology. However, the decision being modelled here is a one off adoption. Having adopted a PV system, the household does not re-evaluate the adoption decision as the timeframe of the simulation scenarios is too short to realistically require further adoption.

Therefore, c_{OUT} is measured as economic benefit and feedback effects from the ease of installation or perceived function are not considered.

6.7.3 Aggregator agent

Although the aggregator agent is not the main focus of this study, it nonetheless has an important role to play in the overall system model. The aggregator agent used follows the design presented in Boait et al. (2013). In this model, its function is essentially to sum the demand of prosumers and thereby provide aggregate output variables for the model.

6.8 Summary

The method of investigation includes statistical analysis of FiT installation data (6.2) in conjunction with the development of a computational model to simulate adoption. An ABM (6.3) has been developed within the CASCADE framework (6.4.1) to simulate technology adoption in the smart grid (6.5), using the household as the adopting agent and fundamental unit of analysis. The

[4]The model has been implemented to allow for probabilistic adoption based on the comparison of c_B with a threshold, but that is beyond the scope of this study)

model incorporates human behaviour alongside technical and economic benefits of the technology via use of the SCT model within agent decision making (6.5.2 & 6.6). The mapping of household characteristics to SCT constructs was performed as outlined in section 6.7.

The data analysis and results are described in Chapter 7, followed by specific parameterisations of the model and their results in 8.

Chapter 7

Analysis of empirical data

The data to inform the parameters required in the model and the likely values they could take were gathered from a number of sources. Quantitative data were obtained for demographic information, installations under the FiT, energy consumption in various geographic regions, typical weather conditions at certain sites in the UK and solar irradiation for the purposes of estimating PV performance. Each of these was analysed and combined in order to estimate the effects of various parameters on the adoption of smart grid enabling technology (specifically distributed renewable generation). In addition, secondary qualitative data on factors affecting personal decisions whether to adopt technology were gleaned from the literature and used to inform the model algorithms.

This chapter describes the data obtained and the methods used to cleanse (where necessary), query, analyse and combine datasets in order to get a comprehensive picture of the UK situation with regard to distributed renewable generator installation. Each dataset is treated in turn, followed by a section on the combination of datasets and finally the conclusion of this chapter describing the implications that it has for the modelling work in hand.

Data is for Great Britain only – despite some data sets describing the whole United Kingdom (GB and Northern Ireland), Energy policy is a devolved power held by the Northern Irish Assembly and at present FiTs are not available in Northern Ireland, where domestic PV have continued to be registered for ROCs.

7.1 FiT registered installation data

The quantitative data for the domestic PV adoption case study used in this research were obtained from the FiT registration database maintained by Ofgem (Ofgem, 2013a)[1]. The analysis

[1] For the initial analysis, the data were obtained via the Renewable Energy Foundation database (REF, 2012) as they were not available from Ofgem, but were latterly obtained directly from Ofgem (Ofgem, 2013a). The two

reported here was conducted in September 2013, and includes data from April 2010 – June 2013 (the data available at that point). Subsequent data and comparison between observed subsequent data and modelled adoption are discussed in Chapter 9.

The data were imported into a MySQL database, allowing complicated queries to be run on the data using the HeidiSQL front end (Becker and Dev Team, 2013). Statistical analysis and plotting was performed in the R statistics package (R Core Team, 2013) using the RJDBC library to link between R and the SQL database (Peidro et al., 2004). In addition, a number of Python (PSF, 2011) scripts were used to perform time-series analysis on data. Finally, MapWindow GIS was used to prepare the geographical visualisations of data and code any GIS scripts necessary to undertake the analysis (MapWindow GIS Team, 2011). The method for each stage of analysis is described below, with detailed SQL statements available in Appendix B and code listings available in Appendix C.

7.1.1 Initial data characterisation

The data consist of one row per registered installation. The basic characteristics of the database are presented in Table 7.1 and Table 7.2 below. It is immediately obvious that the installations registered for the FiT are dominated by photovoltaic installations with 98.6% of the records in the database referring to such installations).

7.1.2 Data anomalies and treatment

FIT_ID duplication The data contained a number of rows which share the same `fit_id`. Inspection of instances where multiple data rows shared the same `fit_id` revealed that they described a situation where the same FiT application has been used to cover installations with differing commissioning dates. There were 4267 `fit_id`'s with more than one data row – the majority of these refer to 2 data rows, whilst the largest encompasses 12 data rows. In total 9086 rows were affected by `fit_id`'s covering multiple data rows, 2.2% of the total database[2]. For the purposes of this analysis, each row is counted as a separate installation – however it is acknowledged that those sharing the same `fit_id` are likely to be related in some way – for instance covering two installations on the same property.

databases are substantively the same, with the only differences being in presentation.

[2] See Appendix sections B.3 & B.4 for SQL to repeat this analysis

Table 7.1: Description of FiT database (See Appendix section B.1 for SQL)

Type of technology	Number of data rows
Anaerobic digestion	53
Hydro	390
Micro CHP	454
Photovoltaic	392470
Wind	4831
Total	**398198**

Table 7.2: Available fields in FiT database (See Appendix section B.2 for SQL)

Data field	Type	Length	Notes
fit_id	varchar	15	
post_code_district	varchar	4	
post_code_area	varchar	2	Derived by the author from post_code_district_above
technology_type	varchar	31	
installed_capacity_kw	float	Default	
declared_net_capacity_kw	float	Default	
application_date	date	Default	
commissioned_date	date	Default	
export_status_type	varchar	31	
tariff_code	varchar	31	

Data field	Type	Length	Notes
description	varchar	12	
installation_type	varchar	31	
country_name	varchar	8	
local_authority	varchar	31	
government_office_region	varchar	31	
accreditation_no	varchar	15	
supply_mpan_no_first_2_digits	int	2	
community_school_category_ applicable_from_01_12_2012	varchar	31	
llsoa_code	varchar	9	Not applicable in Scotland

Geographical information The database has multiple granularities of geographical information, the coarsest being the country in which the installation is situated. In descending order of granularity, geographical information available is the Distributor ID (1st two digits) from the Meter Point Administration Number (MPAN), local authority, postcode district and finally Lower Layer Super Output Area (commonly referred to as either LLSOA or LSOA) - see Figures 7.1a & 7.1b for illustration of two of these scales.

120 data rows contain no geographical data whatsoever. Inspection of these reveal them to be distributed across application and commissioning dates and installed technology types. The reason for these anomalies is not known and these rows are necessarily excluded from any geographical analyses.

8015 data rows (2.0% of database) contain no geographical information beyond the MPAN distributor ID of the meter involved. These are excluded from any GIS analysis which is not specifically concerned with DNO areas.

LLSOA codes apply only to England and Wales – installations in Scotland have llsoa_code = “N/A” in the database. Note that this is distinct from missing information.

Although the overall number of records without geographical information is not particularly high, the possibility that they are concentrated in certain areas cannot be excluded and introduces a small amount of uncertainty in the GIS analyses presented. As the missing geographical information is a small proportion of the database the projected uncertainty will not have significant effect on the conclusions drawn.

Reporting accuracy The data in the installation report are based upon information reported by renewable technology installers. As such, they are subject to the fallibility of any self-reported system, including accidental error and potential deliberate falsification. The installers who register installations are accredited by the Microgeneration Certification Scheme (MCS), providing some protection against these effects, however it is acknowledged that there may be some uncertainty associated with data input error. It is considered that the likely effect of such error will be small and distributed across the data set.

Differences between installed capacity and declared net capacity Some installations have a difference between the installed capacity and the declared net capacity. This difference is usually small.

In a very small number of cases – the declared net capacity is greater than the installed capacity. This case is obviously an error, affecting 175 records in the database (0.04% of database) all of which are photovoltaic installations. Upon inspection, is simply a rounding error with no record exhibiting such an erroneous difference greater than 0.01kWp.

14480 records show a declared capacity somewhat less than the installed capacity. Of these 547 are for non-PV installations. Within the 13933[3] PV records with a lower declared capacity than installed, the minimum difference is 0.01kW, the maximum 998.53 kW on a large commercial installation.

In the rest of this analysis – where capacity is discussed, it is the declared net capacity that is used in calculations rather than the installed capacity as it is this capacity which will be relevant to smart grid operation.

Changes between releases of data The database for FiT installations is released every 3 months. In some releases, records which were present in a prior release are no longer present in the sub-

[3] See Appendix section B.5

sequent release. It is not clear why this would occur. For instance, a comparison between the 30th June release (Ofgem, 2013a) and the 31st March release (Ofgem, 2013b) in 2013 revealed 421 rows that were present in the 31st March database but were either changed or missing in the 30th June database[4]. An examination of these rows shows no obvious connection between them. It is possible that they represent corrections to earlier input errors as referenced in section 7.1.2 – there is a mechanism by which microgeneration certificates, which form the basis of the data, may be amended (MCS, 2013).

7.1.3 Effect of changes to classifications over the lifetime of FiT

Some of the policy changes discussed in Chapter 3, mean that the allowable data values in some of the fields has changed over time. In particular, the tariff bands for photovoltaic installations changed significantly on 3rd March 2012, introducing the mechanism to vary PV tariffs separately from other types ofrenewable generators as well as reclassifying the capacity boundaries for PV installations (Ofgem, 2013c); Tariff Table 1 August 2012. From 1st December 2012, the regulations regarding installations registered as community installations changed significantly – with such installations attracting a different tariff to similar installations registered as commercial or domestic and, where they are attached to a building, requiring the building upon which they are installed to achieve at least a "D" rating for energy efficiency on its Energy Performance Certificate (EPC) (Ofgem, 2013d, paragraph 2.78). More recently, proposals have been made to increase the capacity threshold for such installations beyond 5MW (DECC, 2013c; UK Government, 2013).

The effect of these changes can be clearly observed in the database – and are dealt with the in the analysis where necessary.

7.2 Extraction of data for PV case study

The database was queried for installations of type photovoltaic only (Table 7.3). This shows that in terms of number of installations, the PV domain is dominated by domestic installations. In terms of capacity, domestic installations still form the vast majority of the capacity, however commercial non-domestic installations are significant – contributing just over 20% of the capacity. This is not surprising, as it is likely that commercial installations will be on a larger scale

[4]See Appendix section B.6

than domestic installations. A typical roof face suitable for PV installation might be around 30 m2, with PV panels typically generating just over 100Wp/m^2, resulting in ∼3kWp installations on domestic dwelling rooftops. The data show that the average domestic installation declared capacity is 3.27 kWp, whereas the average commercial is 35.7 kWp.[5]

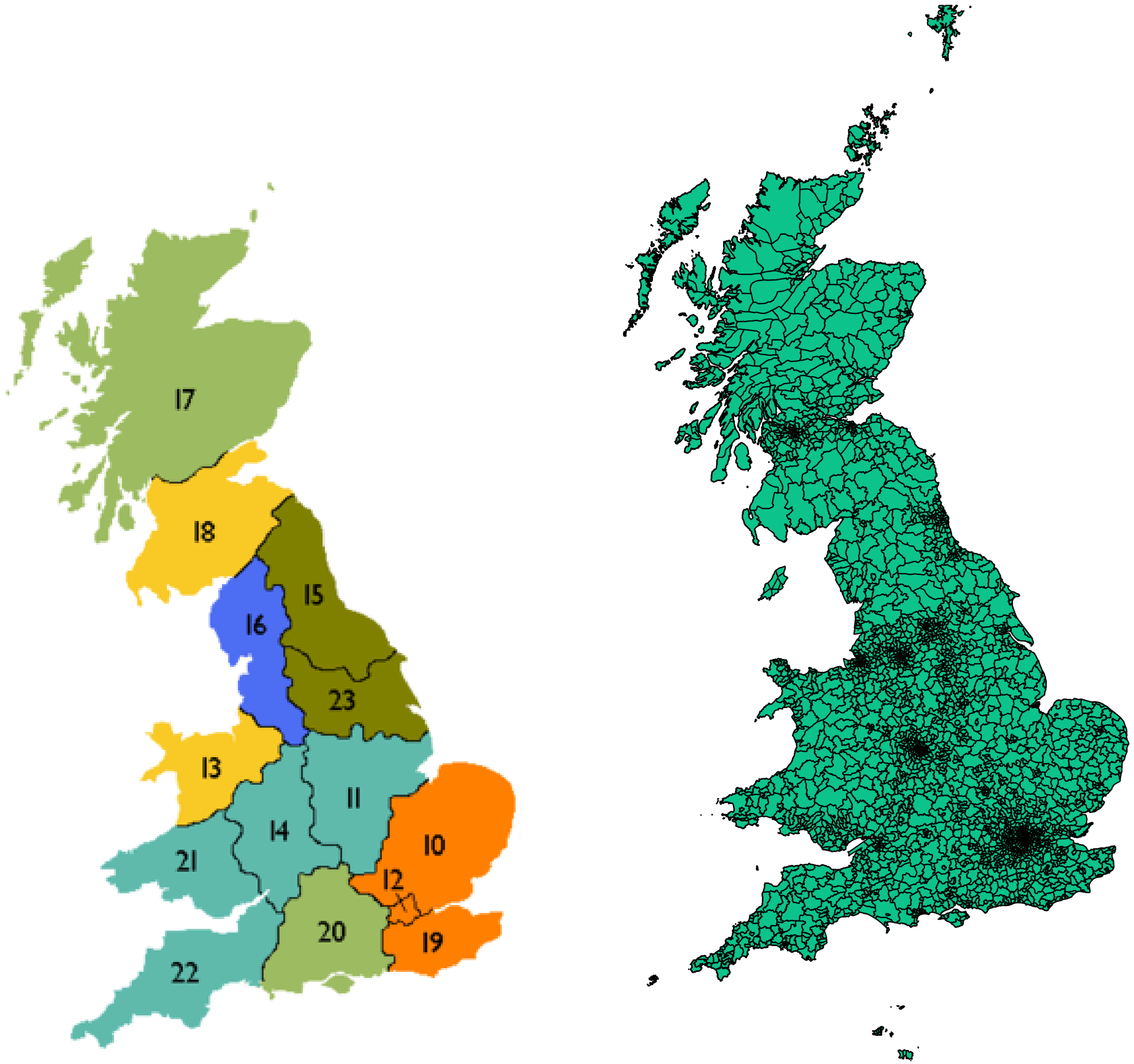
Table 7.3: Basic description of photovoltaic installations registered for FiTs

Type of installation	Sub-type	Number	Capacity (kWp)	Mean capacity per installation (kWp)
Community	-	1735 (0.44%)	18623.1 (1.12%)	10.73
Domestic	-	380158 (96.86%)	1242647.7 (74.86%)	3.27
Non Domestic	Commercial	9951 (2.54%)	355222.4 (21.40%)	35.70
	Industrial	626 (0.16%) (0.16%)	43430.5 (2.62%) (2.62%)	69.38
All		**392470**	**1659923.7**	

7.2.1 Distribution of PV installed capacities

A histogram (bin width = 0.05 kWp) of installation capacities reveals the distribution of installation (Figure 7.2).

[5]See Appendix section B.7



(a) Coarsest geographical aggregation: Electricity Grid Supply Distributor IDs

(b) Intermediate geographical aggregation: Post-code districts

Figure 7.1: Different geographical resolution available in the Feed-in Tariff database

Plotting a similar distribution for domestic installations (Figure 7.3) shows a distinct peak at 4kWp installations – this is predictable as there has been a sharp decrease in tariff rate for installations with a capacity higher than 4kWp since the introduction of the FiT. The data show there to be a small number of very high capacity installations registered as "Domestic". It is not clear whether these are in fact data errors, or represent unusual cases such as home-owners with large areas of land installing large systems

Figure 7.2: Histogram showing the distribution of PV installation capacities

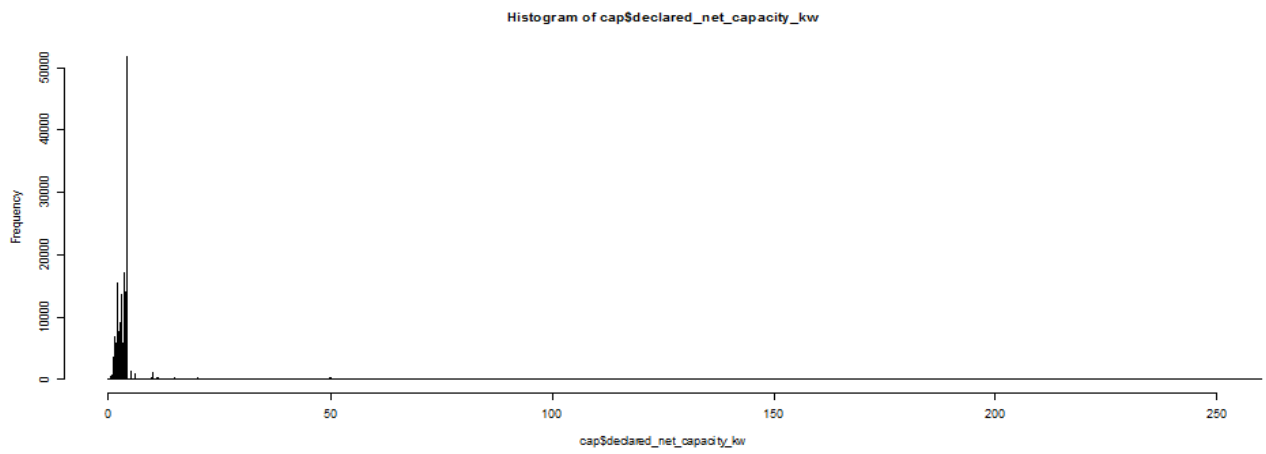
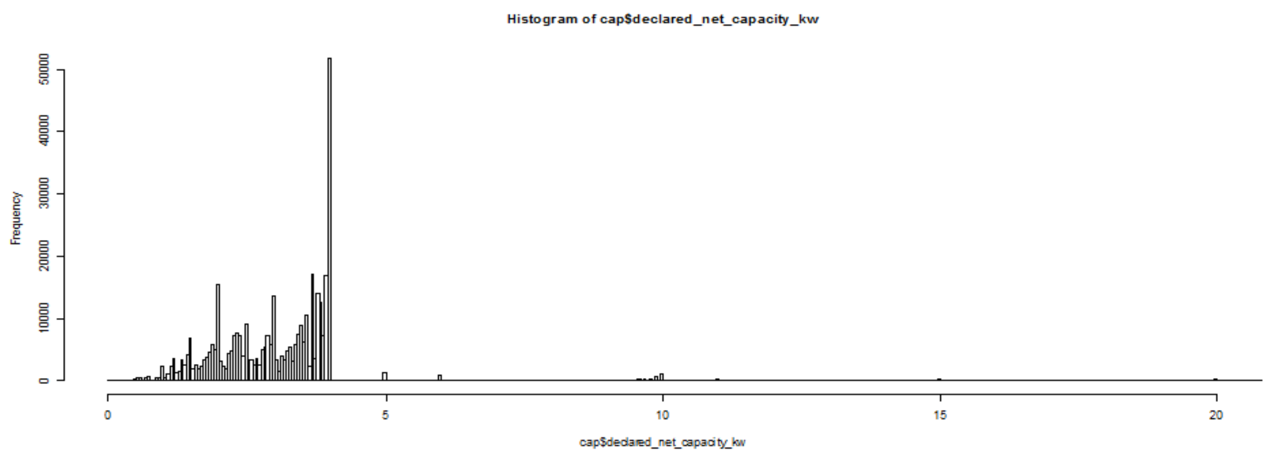


Figure 7.3: Histogram showing the distribution of domestic only PV installation capacities



It can be seen that the distribution of declared capacities is clustered around quantized steps (which is to be expected as installations will tend to be a certain number of common panel sizes). Descriptive statistics for the declared net capacity of domestic installations as of June 2013 confirm that the notable peak is at 4.0 kWp, with both mean and median capacity are both just over

3.0 kWp (Table 7.4). These observations are used to parameterize the capacity of installations in the adoption model developed during this research.

Table 7.4: Descriptive statistics of domestic PV installation capacity

Minimum capacity	0.100 kWp
1st Quartile	2.250 kWp
Median	3.180
Mean	3.333
3rd Quartile	3.840
Maximum	1063.000
The modal value is 4.0 kWp with 37611 installations being declared at 4.0 kWp exactly; 74222 with 3.9 < `declared_capacity` <= 4.0 kWp.	

7.2.2 Temporal distribution of PV adoption

Examination of the pattern of adoption over time is crucial to understanding the transient effects, both positive and negative, of such adoption on the electrical distribution grid. Both cumulative adoption and rate of adoption were examined using three different temporal granularities (daily, weekly and monthly). These were examined for both number of installations and capacity and for domestic only as well as all photovoltaic installations. The time series were constructed using the `installation_date` field from the database (rather than the FiT registration date as installations may be registered long after they are installed).[6]

Inspection of the time series revealed a number of interesting phenomena. Firstly, the appropriate timescale over which to consider the series was determined. If the series are plotted daily (Figure 7.4 (top)), a rather uninformative weekly pattern of fewer installations over weekends is observed – this will occur for trivial reasons due to the typical working pattern in the UK. Therefore further analysis does not consider the daily pattern of adoption.

However, the monthly pattern of adoption (Figure 7.4 (bottom)), whilst widely used in govern-

[6] Note that preliminary accreditation - introduced 2012 for ROO-FIT (>50kW) installations does not concern us in this study as they do not affect the vast majority of domestic installations

ment reporting, smoothes some important features of the time series, not capturing the sharp spikes which occur, apparently in response to some event. Therefore, further analysis of time series in this study will use a weekly timestep (Figure 7.4 (middle)) unless explicitly specified.

It is immediately noticeable that the rate of adoption (i.e. number of installations commissioned per week) exhibits a number of sharp "spikes" in installation, rather than a smooth increase (and potentially decrease) in rate of adoption as might classically be expected in models of technology diffusion or adoption (Bass, 1969; Norton and Bass, 1987; Rogers, 1983)

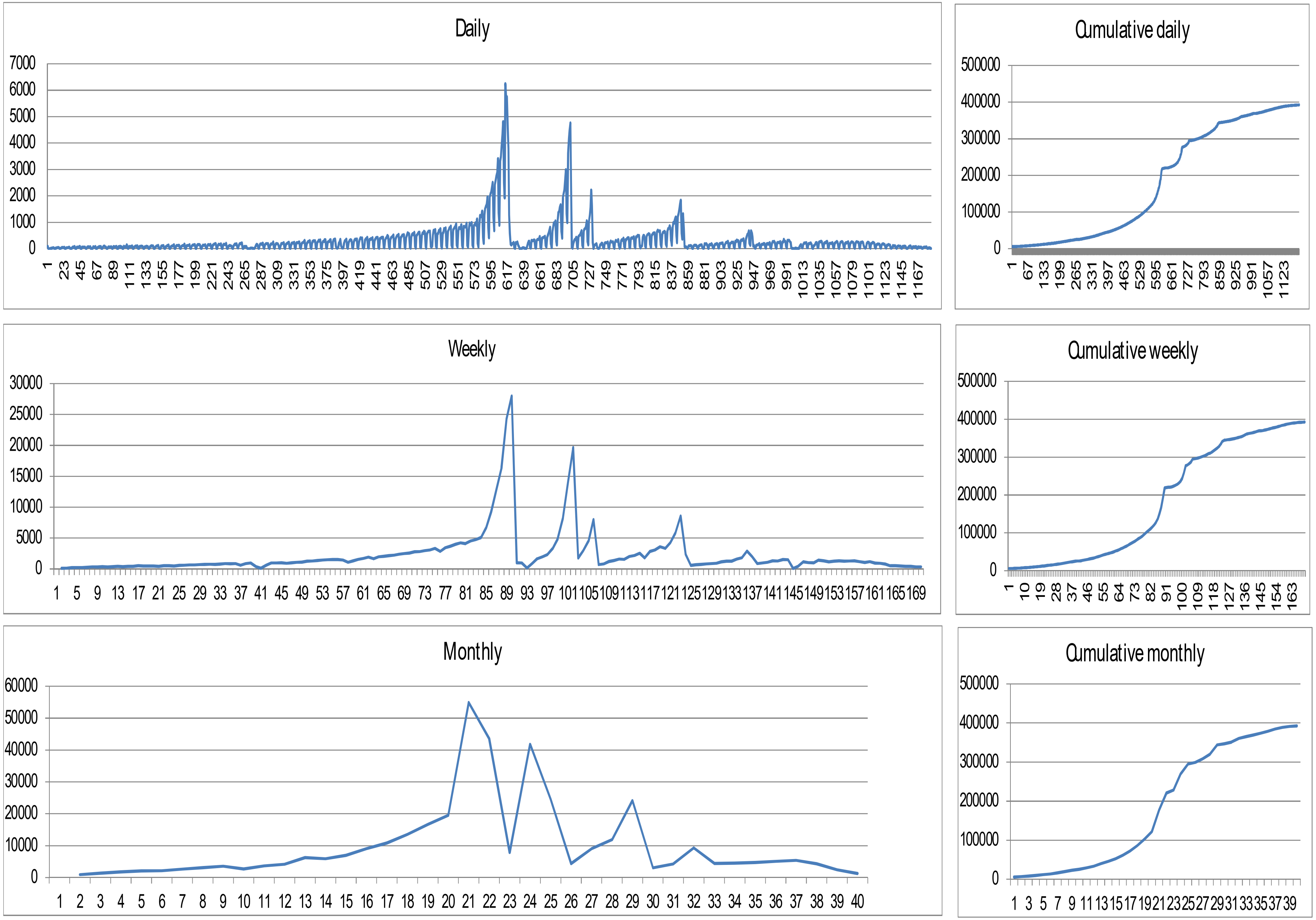


Figure 7.4: Time series of PV installation April 2010 – June 2013 at daily, weekly and monthly temporal resolution. Adoptions per time period (rate) shown on the left - cumulative adoption on the right.

An analysis of the dates of the spikes in adoption reveal that the first (and largest) spike in the rate adoption started in the week commencing 6th November 2011 and reached its peak in week commencing 11/12/2011 before collapsing in week commencing 18/12/2011. This was followed by a similar pattern (albeit smaller scale) repeated 4 times (Figure 7.5 & Table 7.5).

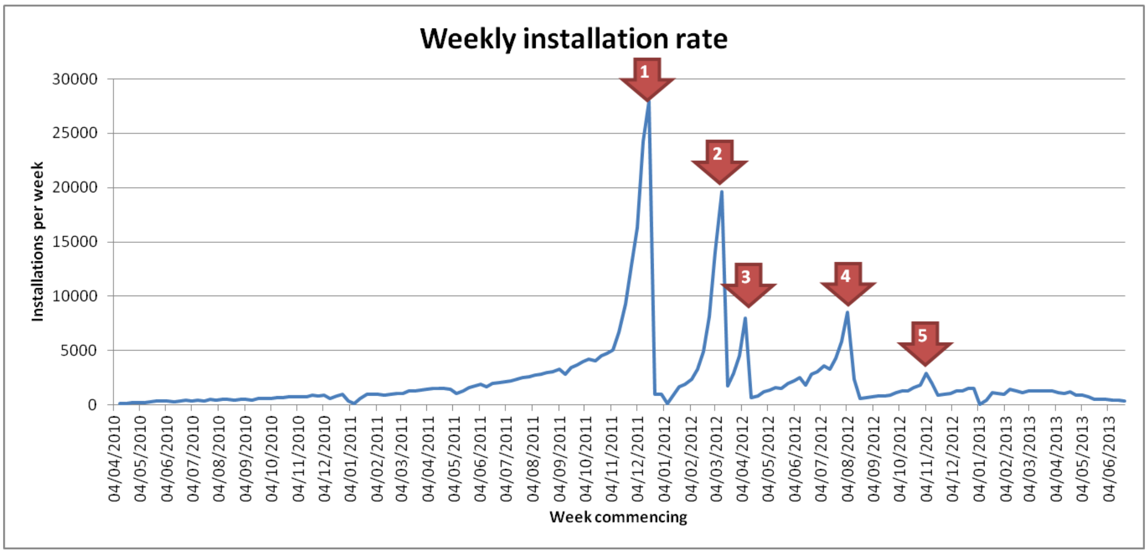


Figure 7.5: Rate of PV adoption with spikes highlighted

The reasons for this pronounced pattern were investigated and it was found that the dates of the spikes correlated with the announcements of policy changes in the FiTs (Table 7.6). It is notable that, in the case of the largest spike (1 in Figure 7.5), the spike was generated by the announcement and probable loss of perceived benefit, as the actual change to FiT rate did not occur on the announced date, 12^{th} December 2011, due to a challenge to the legality of retrospective changes to tariffs (EWCA Civ 28, 2012). This highlights the fact that, despite the strong economic rationale behind trying to install a system before detrimental changes were made to the tariff rates, the spikes cannot easily be modeled using classical rational economics techniques as, on the face of it, nothing has changed in the rational evaluation of the case for installing PV prior to December 2012.

Table 7.5: Data on the PV adoption rate peaks

Peak number	**Peak start**	**Peak end**	**Peak rate (installations per week)**
1	13/11/2012	25/12/2012	27990

Peak number	Peak start	Peak end	Peak rate (installations per week)
2	12/02/2012	08/03/2012	19637
3	25/03/2012	15/04/2012	7978
4	22/07/2012	19/08/2012	8565
5	04/11/2012	18/11/2012	2895

A similar pattern to that observed for the UK (Table 7.6) is seen in Germany, as reported in the scientific literature (Leepa and Unfried, 2013) and described by the head of the German statistical agency:

"Previous experience has shown that the cut-off date mechanism leads to a significant increase in the number of PV systems installed shortly before support measures are cut. This effect counteracts the intention of the legislator to effectively limit the costs of support for solar power."

Source: (Bundesnetzagentur, 2012)

It is, of course, possible that a certain proportion of installations reported as being installed and commissioned somewhat earlier than they actually were in order to take advantage of the higher rate. Whilst such fraudulent reporting cannot be entirely discounted, it is unlikely to account for the entirety of the effect.

A final point to note in regard to the time series of adoptions is that as of June 2013, the rate of adoption since 21st April 2013 was consistently been below 1000 installations per week. Whilst there were short periods of such relatively low installation rates between the spikes discussed in the previous paragraph, the last time the rate was consistently below that level was prior to February 2011. This appears to indicate a stabilisation in the rate of adoption of photovoltaics in the UK – suggesting that the adoption triggered by the introduction of FiT is reaching the end of the traditional cycle of adoption. This implies that, in the absence of further incentives or disruptive events, further adoptions will be at a relatively low rate and represent the quiescent number of adoptions expected in a mature market. In other words, the S-Curve of cumulative adoption shown in Figure 7.4 has reached its upper corner height and we are now in the phase where there is a slow quiescent adoption in the wide population (characterised as "Laggards" by

Table 7.6: Correspondence between policy change, announcement date and PV adoption rate peaks

Policy change	**Date announced**	**Due to be effective for installation after**	**Actual date of change**	**Peak in Figure 7.5**	**Notes**
Extraordinary review of tariff rates	31st October 2011 (EWCA Civ 28, 2012, para. 6)	12th December 2011 (EWCA Civ 28, 2012, para. 8)	N/A	1	This implementation date for the reviewed tariffs was challenged in court and did not become effective until 1st April 2012 (see below)
Implementation of revised tariffs for PV installation	13th January 2012	1st April 2012	1st April 2012	2&3	Announcement of result of legal challenge (EWCA Civ 28, 2012). Note that Easter intervened between peaks 2&3
Second review of tariffs	9th February 2012	1st August 2012	1st August 2012	4	Tariff reviews now to occur at 3 monthly intervals
First of the 3 monthly tariff reviews	1st August 2012	1st December 2012	1st December 2012	5	

Rogers) in the absence of further stimulus.

7.2.3 Geographical distribution of installations

The geographical distribution of technology adoption is useful in order to understand the potential local effects of supply and demand balance and how these might alleviate or exacerbate issues with distribution network overloading in a potential smart grid. To this end, the adoption data were plotted per postcode district and per Lower Level Super Output Area (LLSOA) using GIS software. Boundary data for the LLSOA and postcode districts were obtained from the UK Data Service Census Support service offered to academics via EDINA (Ordnance Survey, GB, 2010) in ESRI shapefile format.[7] LLSOA boundaries used in presenting geographic data were those for the 2001 census as these are how the FiT database is encoded, despite the more recent 2011 census LLSOA boundaries being available. These are similar, but not identical to, the boundaries for the 2001 census – for instance there are 34753 LLSOA's used to classify the 2011 Census compared to 34378 in 2001. Details on the changes may be found via the Office for National Statistics website (ONS, 2013), however do not materially affect the analysis in this section and subsequent conclusions.

Firstly, a postcode district level analysis was undertaken. This covers the whole of Great Britain. One postcode district was present in the FiT installation file but not in the geographical map of postcode districts – this was CR9 which, upon investigation, was found to be a non-geographic postcode with the buildings registered to CR9 being actually located in CR0. Thus, the totals for CR9 were added to those for CR0. There were a total of 7088 PV installations (1.8% of all PV installations) with no postcode information (Table 7.7). These represent a total capacity of 312826 kWp (18.8% total capacity), indicating that large installations such as PV farms are over-represented in this group. Large commercial schemes in general do not appear to have postcode information associated with them – 66% of the installed non-domestic capacity does not have geographical information associated with it – with 272 of the 285 non-domestic installations rated over 100kWp falling into that group. This means that analyses of installed capacity in an area and the match between that and localized demand must acknowledge that such installations are outside the analysis.

[7] The following copyright statement applies to this data *"This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown."*

Table 7.7: Photovoltaic installations by type and availability of postcode geographical information

installation_type	**Postcode district available?**	**Number of installations**	**Total declared capacity (kWp)**
Community	No postcode	330	4719.0
	Postcode available	1405	13904.1
Domestic	No postcode	5104	39578.4
	Postcode available	375054	1203069.3
Non Domestic (Commercial)	No postcode	1482	235091.5
	Postcode available	8469	120131.0
Non Domestic (Industrial)	No postcode	172	33437.3
	Postcode available	454	9993.2
Total	**No postcode**	**7088**	**312826.2**
	Postcode available	**385382**	**1347097.5**

A similar analysis holds for geographical information at the LLSOA level (Table 7.8).

installation_type	LLSOA data available	Number of installations	Sum of declared capacity (kWp)

Table 7.8: Photovoltaic installations by type and availability of LLSOA geographical information (Scotland excluded)

installation_type	LLSOA data available	Number of installations	Sum of declared capacity (kWp)
Community	No LLSOA	341	4827.3
	LLSOA available	1350	13172.4
Domestic	No LLSOA	8375	45583.0
	LLSOA available	346389	1112815.5
Non Domestic (Commercial)	No LLSOA	1674	236130.5
	LLSOA available	7879	113962.8
Non Domestic (Industrial)	No LLSOA	174	33470.1
	LLSOA available	438	9677.9
Total	**No postcode**	**10564**	**320010.9**
	Postcode available	**381906**	**1339912.9**

As of June 2013, there were also 50 commercial photovoltaic installations in England, Scotland and Wales[8] registered under the Renewable Obligation Certificate (ROC) scheme rather than the FiT scheme. Due to these problematic omissions from the data set, combined with the modelling focus on domestic agents, the geographic analysis was performed for domestic installations only.

Shapefiles could be obtained describing the boundaries for individual countries - England, Wales (ONS, 2001a) and Scotland (GRO Scotland, 2001a). These were merged using GeoMerge (VDS Technologies, 2007) and data from the installation database described above added to the

[8] All PV installations in Northern Ireland are registered in this way.

GIS database (.dbf) file using DBFNavigator (Dolgachov, 2002). During initial exploratory analysis chloropleth maps for the absolute number of installations (for domestic installations only) were plotted[9]. These were plotted for weekly snapshots with the number and capacity of installations for each geographical unit being calculated from the database. Extracting a small number of such snapshots can give a useful picture of the pattern of adoption over time and space. For instance, if five snapshots across the first three years of the scheme are considered (see Figure 7.6) , it is easy to observe the rapid rise in the number of adoptions seen between early 2011 (Figure 7.6b) and 2012(Figure 7.6c) as described in Section 7.2.2, as well as an interesting geographical distribution. During this research, a tool to visualise this dataset as a video was developed, which shows these effects particularly strikingly. The code to do so is made available at the repository previously linked and a sample output video showing the sequence illustrated in Figure 7.6 is available at `https://www.youtube.com/watch?v=YYrsXf92jBo`

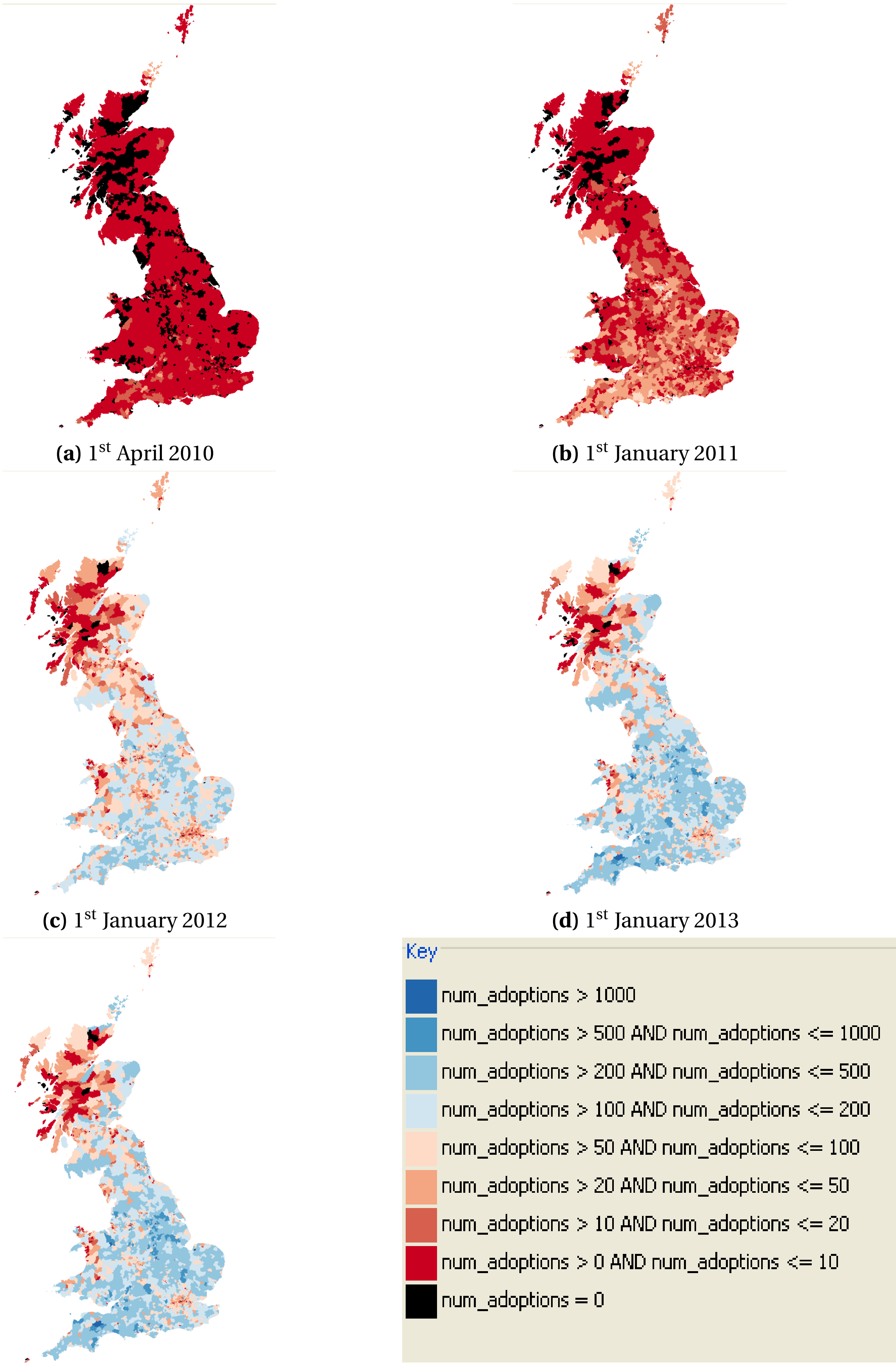
This analysis and visualization shows that the areas of the country with relatively large numbers of PV installation have remained similar over time (although the total number of installations has risen markedly, the distribution is similar). It also highlights the fact that both the total number of installations is low in large conurbations (e.g. London, Birmingham, Manchester).

The same analysis was undertaken at LLSOA level (Figure 7.7 - note the factor of 10 change in scale due to the change in scale of geographical unit) and shows a broadly similar pattern, with the low level of adoption close to city centres being even more apparent.

7.3 Localised Energy use data

Disaggregated energy use data were obtained at Local authority, MSOA and LLSOA level (DECC, 2011b). These were used to investigate a comparison of domestic PV installation capacity with domestic consumption at a local level. For reasons of privacy, some categories of localised energy data could not be published at the individual LLSOA level as to do so would potentially identify individual consumers. In these cases DECC have amalgamated results for two LLSOAs as described in their methodology and guidance (DECC, 2013a). This method has been employed mainly where the number of Economy 7 meters in a given LLSOA is small. These meters are ignored in this analysis as they form a very small fraction of the meters responsible for total con-

[9]Example SQL for one snapshot of installations per geographical area is given in Appendix section B.8



(a) 1st April 2010

(b) 1st January 2011

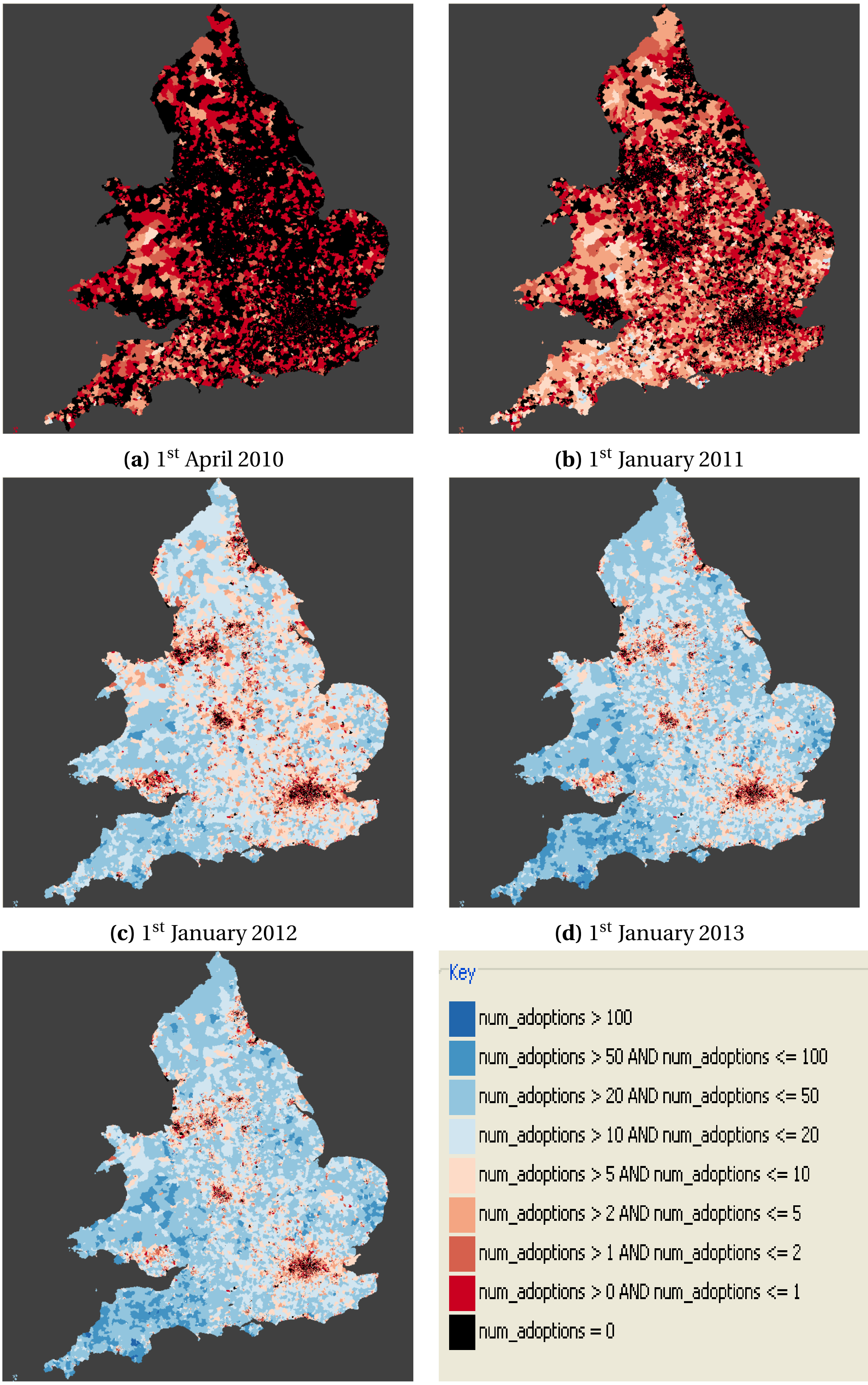
(c) 1st January 2012

(d) 1st January 2013

(e) 30th June 2013

(f) Key

Figure 7.6: Snapshots of installations per postcode district (e.g. LE2, M11...). Each map is a snapshot in time



(a) 1st April 2010

(b) 1st January 2011

(c) 1st January 2012

(d) 1st January 2013

(e) 30th June 2013

(f) Key

Figure 7.7: Snapshots of installations per LLSOA. Each map is a snapshot in time

sumption; hence their effect on average consumption in the LLSOA is unlikely to be significant.

Comparison of domestic PV installed capacity with local energy use was made, to investigate the relationship between geographical areas of high usage and areas of high domestic penetration of domestic PV generation (see section 7.6).

7.4 Demographic data

As the geographical distribution of adoption was seen to be uneven over the country, demographic data was obtained and analysed in order to examine the potential links between socio-economic factors and adoption in local areas. Census data were obtained at Output Area and LLSOA area, including the usually resident population in an area, the number of households in that area, the area classification, Socio-economic classification and tenure of households. These data were downloaded from CASWEB (ONS, 2001b; GRO Scotland, 2001b). LLSOA boundaries for the 2001 census were used in preference to the 2011 census LLSOA boundaries as these correspond with the LLSOA data input into the main PV adoption dataset described above. There are 34378 LLSOA areas in England and Wales (2001 census) and 2736 geographical Postcode districts in England, Wales and Scotland.

Census data are available for Output Area (OA) and LLSOA, but not usually at postcode district level. Where such data were required, data were converted from OA to Postcode district using the GeoConvert tool (UK Data Service, 2013). The converted data for postcodes were cross checked with the raw data obtained from the UK Data Service (ONS, 2001c) which provides headcount and household count for postcode districts in England and Wales only. The converted data were found to correspond to the data obtained directly well, with 90% showing discrepancies of less than 2% and 65% with discrepancies less than 0.5%. For this reason, it was considered valid to use the converted data in order that the analysis might be extended to Scotland, for which postcode headcount data could not be directly obtained

As well as basic demographics, such as population, population density and household tenure, an indicator of the wealth of households was sought. This was required as literature suggests that access to capital can be a significant barrier to adoption, so wealth could be a strong explanatory variable for adoption. Direct measures of wealth were not available, howwever Indices of Multiple Deprivation (IMD) – a derived measure of the deprivation of the area - were obtained as an indicator of the poverty levels in LLSOAs. These poverty levels were treated as an inverse proxy measure of wealth (i.e. a positive correlation between adoption and wealth might be expected, so we could expect a negative correlation bewteen IMD and adoption level). This relationship is tested in section 7.6.

DECC's own socio-economic data to combine with the localized energy use statistics (see 7.3) were utilized (DECC, 2013b). These were analysed in combination with the adoption data. It should be noted that no IMD score or resulting analysis could be created for the postcode district level analysis as no valid method is available to convert the IMD scores for each LLSOA into representative figures for a postcode district.

7.5 Weather and insolation data

Weather data for this study were the Test Reference Year (TRY) weather data produced by CIBSE. Of the 14 sites for which weather data are published, the specific dataset used were those for London.[10]. These were used to obtain representative time series for the electricity generation from installed PV panels.

In addition the EU JRC data on average insolation across the UK (Šúri et al., 2007) was obtained to provide some validation for the range of values for insolation data in weather files.

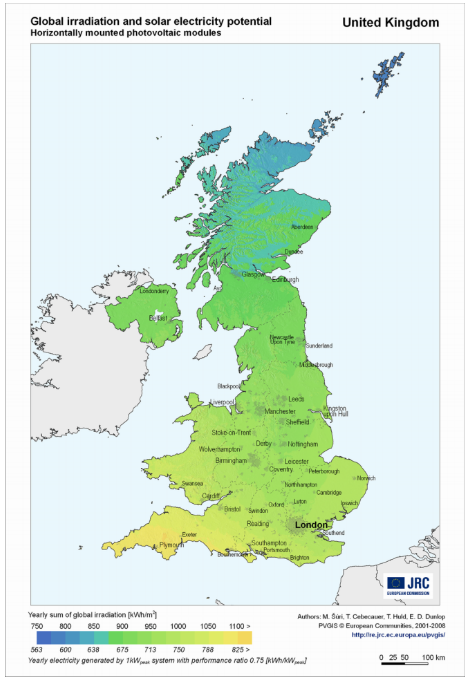
Lowest average insolation levels for the UK are seen in the far North East, whereas highest insolation levels are observed in the far South West. The JRC data corresponds closely with the average insolation data for the TRY and so the data used are considered suitable for this work.

Interestingly, but unsurprisingly, the patterns of highest insolation correspond generally to the areas displaying consistently higher installation of domestic PV (see the similarity in distribution between Figures 7.8a & 7.8b and Figure 7.7).

7.6 Combination of datasets

Most of the datasets could be referenced to LLSOA. The various datasets were combined into one database at LLSOA level, with each LLSOA having the number and capacity of installations

[10] CIBSE Station No 10: London: (filenames start HEB)
Synoptic data: Heathrow: Lat: 51.48°N; Long: 0.45°W; Altitude: 24 m
Radiation data: Bracknell: Lat: 51.38°N; Long: 0.78°W; Altitude: 74 m



(a) UK total insolation in the Horizontal plane

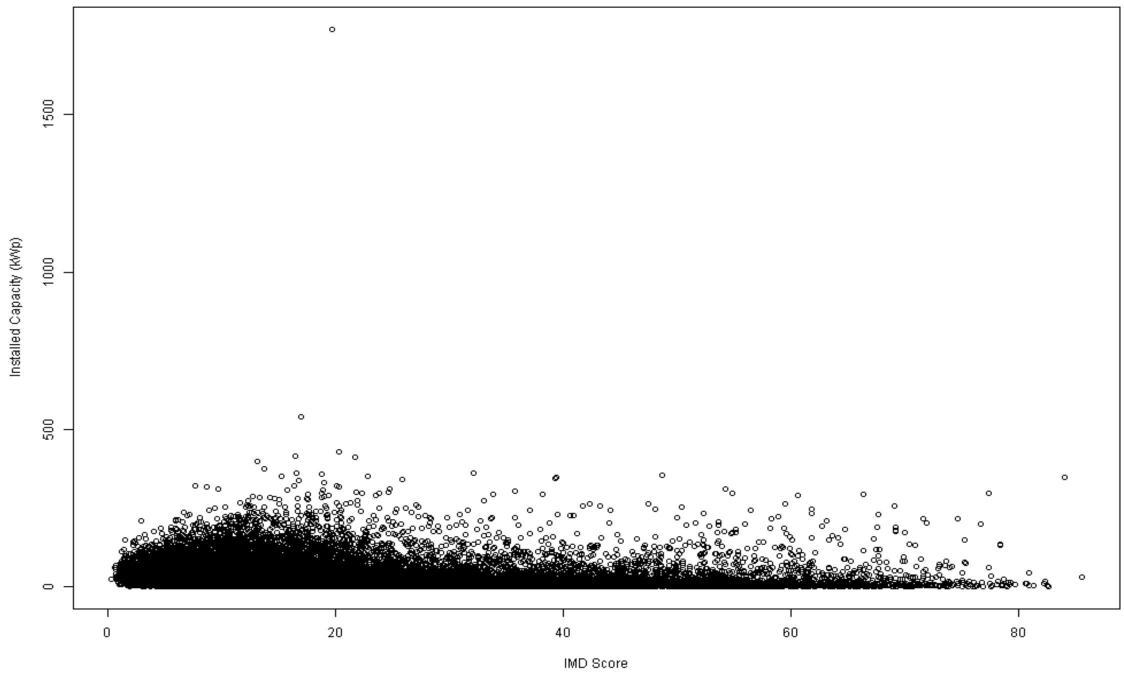
Source: JRC

(b) UK total insolation at optimal angle

Source: JRC

Figure 7.8: UK total insolation (horizontal plane and optimal angle)

Figure 7.9: Scatterplot showing capacity of PV installations as a function of IMD score for each LLSOA



at snapshot times alongside demographic data and energy consumption data as described in sections 7.4 & 7.3 respectively. Test were carried out to investigate whether there were simple relationships between either number of installations, density of installations or capacity installed and other bulk statistics for the LLSOA, such as population or household density, IMD or ownership statistics.

It has been claimed that the FiT has in effect provided a subsidy to those who can afford to install microgeneration, which is paid for by all electricity consumers e.g. (Leicester et al., 2011). This would lead to an hypothesis that microgeneration adoption would be well correlated with the IMD score (negatively, as a high IMD indicates a prevalence of multiple deprivations in a given LLSOA). To test this, scatterplots against capacity installed were produced at the LLSOA level (Figures 7.9 & 7.10). Whilst the plot does show a correlation in the direction expected – a linear regression shows a high probability of correlation ($p < 2.2*10^{-16}$), but a very low proportion of the variation in installed capacity can be explained by the IMD score ($R^2 = 0.02$). This re-affirms the conclusion that the factors driving microgeneration adoption are more complex than simply the economic potential of the LLSOA.

A similar plot was produced in order to assess whether owner occupancy was a determin-

Figure 7.10: Region of interest from Figure 7.9: Capacity of PV installations as a function of IMD score for each LLSOA (plotted without outlier E01020535 which reports a domestic installed capacity of 1.8MW)

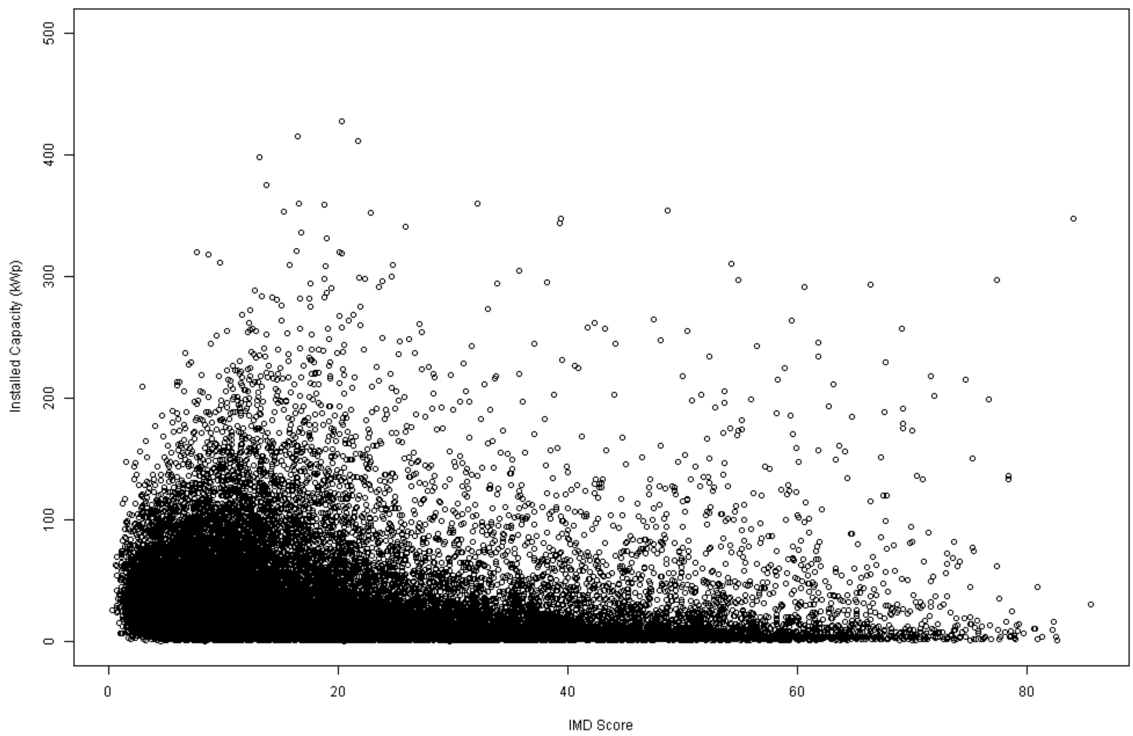
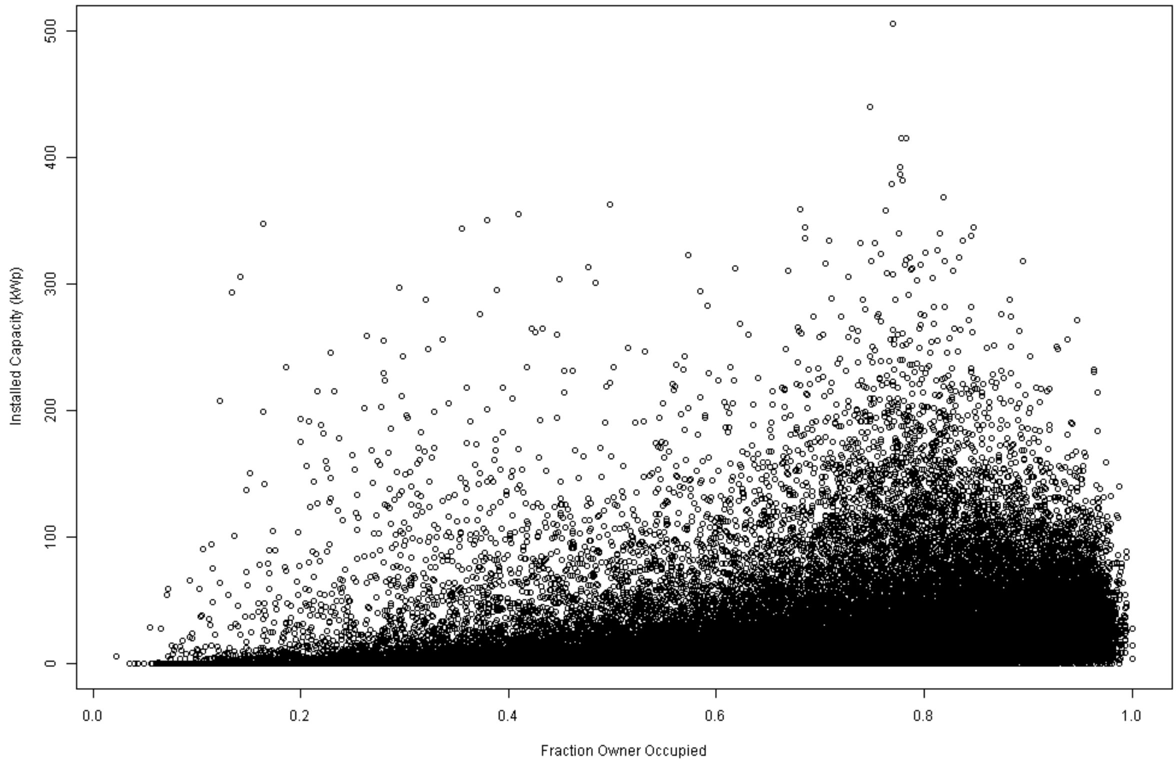


Figure 7.11: Capacity of installed domestic PV against the fraction of housholds that are owner occupied per LLSOA (E01020535 omitted as outlier)

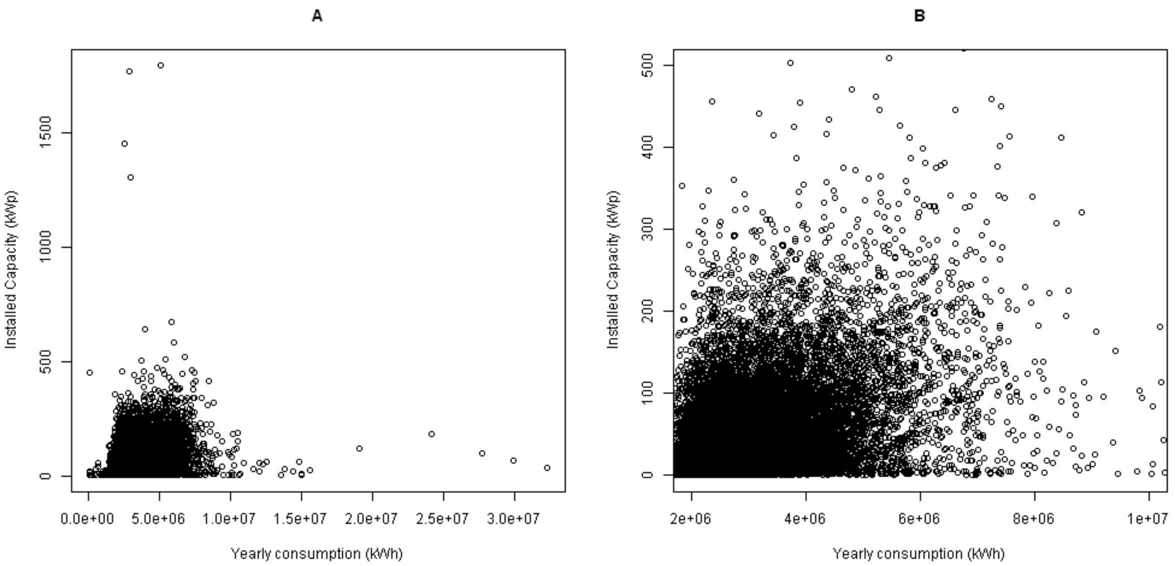


ing factor in PV installed capacity (Figure 7.11). Again, while there appears to be a correlation between these variables (a linear regression t-test gives a p value $< 2.2*10^{-16}$), the fit is poor and the independent variable explains only a small part of the variation in the installed capacity (the linear regression reveals an R^2 value of only 0.0473).

Next, a scatter plot of local energy use and PV capacity installed at the LLSOA level (Figure 7.12) was produced. This indicates that there is a correlation between local consumption and PV penetration, but there is not a strong explanatory relationship between the variables (for linear regression $p < 2*10^{-16}$, $R^2 = 0.13$). p here takes its usual meaning in regression - i.e. the probability that there is no correlation between the variables (the null hypothesis). The extremely low p is due (at least in part) to the extremely large sample size. The low R^2 is of more interest here, this means that many points are far from the regression line and the explanatory power of any observed correlation is low.

This result has implications for visions of a smart grid which incorporate grid balancing at a local level. Individual microgenerators will necessarily reduce net consumption of the household

Figure 7.12: Scatterplots of electricity use in LLSOA against installed domestic PV capacity. (A) all data points (B) outliers removed



in which they are installed however, at the level of penetration observed, they will fall far short of localized grid balancing and the geographical placement of installations is not well correlated with the geographical location of high consumption.

Finally, the relationship between population and household density and PV installation was investigated. Household density can be considered a proxy for a number of variables which influence the suitability of domestic PV installation, for instance multiple occupancy of a building, building density and resultant shading etc. At LLSOA level, a relationship can be observed between household density (households / hectare) and PV installed capacity. This nature of this relationship appears to be inverse exponential (Figure 7.13).

To investigate the strength of this relationship the logarithm of installed capacity was plotted against household density and a regression carried out (Figure 7.14). Again, the relationship appears weak but present ($p < 2 * 10 - 16, R^2 = 0.24$). The correlation with density *does* explain more of the variation than any other variable explored and is thus a factor which should be considered, however it is insufficient to describe the variation between areas in itself.

Again, time series chloropleth maps were plotted for the expression below evaluated in each LLSOA (Figure 7.15).

$$\frac{10 \cdot P_{peak}}{\rho_{households}} \tag{7.1}$$

Figure 7.13: Installed domestic PV capacity as a function of Households per Hectare in each LLSOA

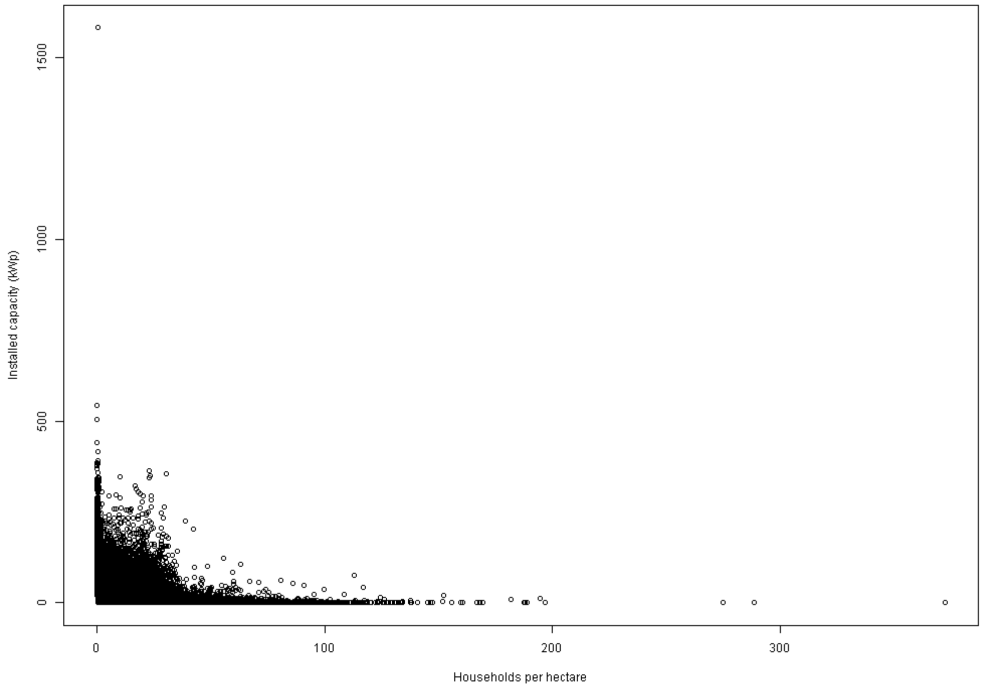
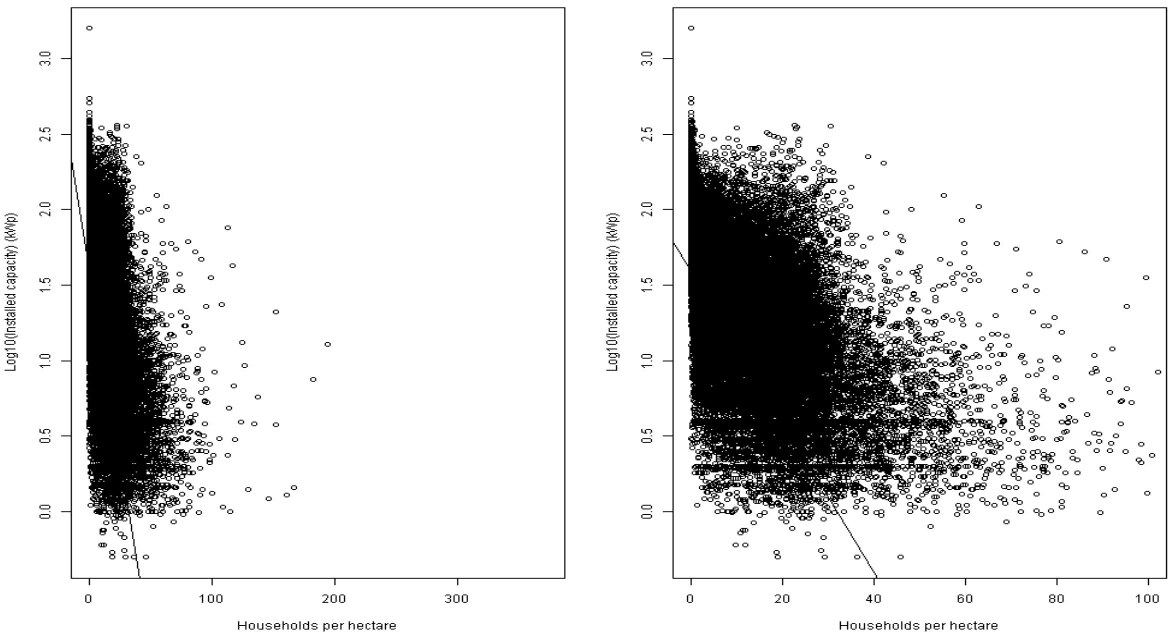


Figure 7.14: Logarithm of installed domestic PV capacity as a function of household density



where

P_{peak} = sum of installed capacity in the LLSO (kWp)

$\rho_{households} = \frac{N}{A}$

N = number of households in LLSOA

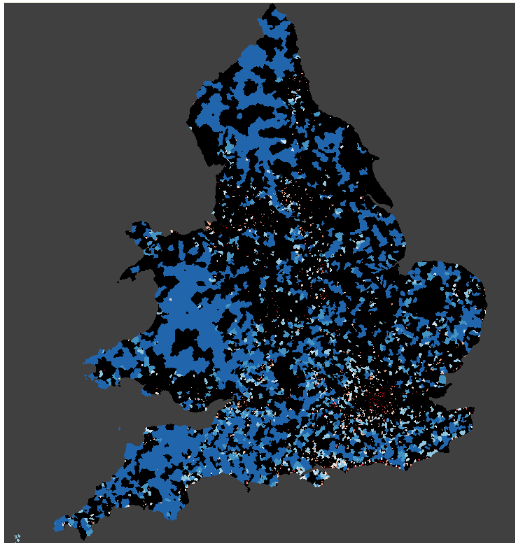
A = Area of LLSOA (m^2)

The variable calculated according to equation (7.1) is labeled `capPerHousePerM2` in the legend of Figure 7.15.

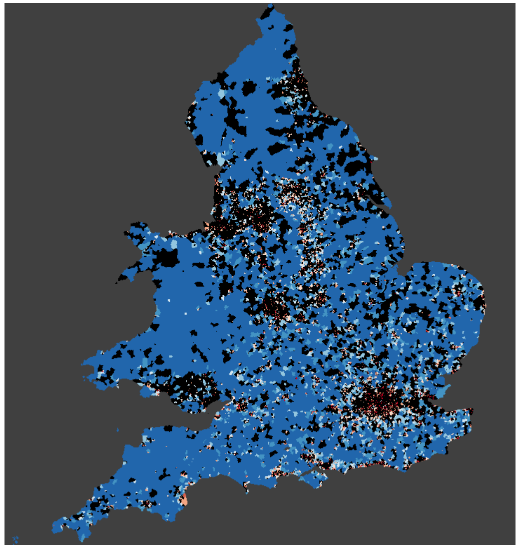
As would be expected from the correlation identified – across most of the country this produces a more homogenous colouring. However, the identification of low installation rates in city areas is more stark.

7.7 Appropriate spatial resolution

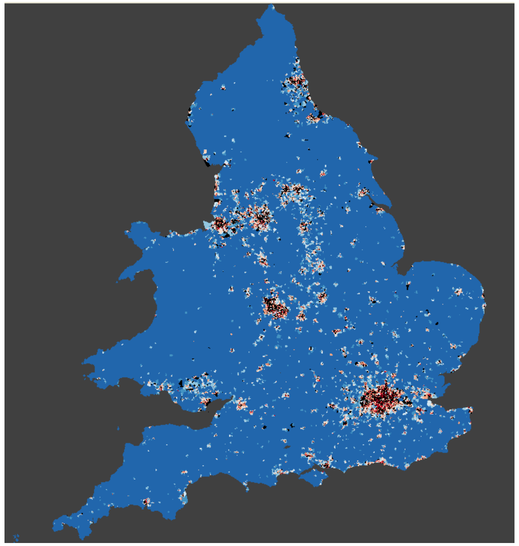
An important criterion to investigate for the modelling activity was the relevant spatial scale at which to model. This is often an issue for modellers and the spatial scale chosen is often justified by pragmatic or intuitive arguments. Instead of relying on such arguments, particularly as the data presents the opportunity for analysis on four different spatial scales, a method to formalise this decision was developed. The pattern of adoption in each local area was compared for similarity to the national pattern of adoption. This was done in order to determine whether it was sufficient to model a postcode area and make the claim that the national picture was a scaled version of this (albeit different postcodes would have different scaling factors as demonstrated by the geographical analysis in section 7.2.3). The same analysis was repeated at LLSOA level. The potential problem was to define a rigorous statistical measure of similarity between timeseries as, for example, a simple least squares measure of fit can exhibit high levels of fit for a pattern that exhibits similar average behaviour but a very different temporal pattern or *shape*. This is illustrated graphically in figure 7.16.



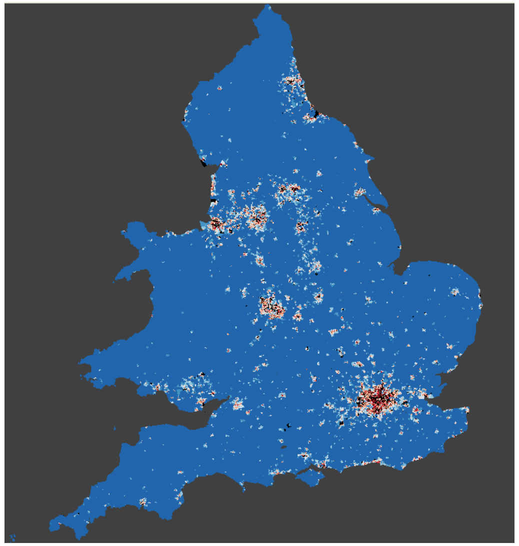
(a) 1st April 2010



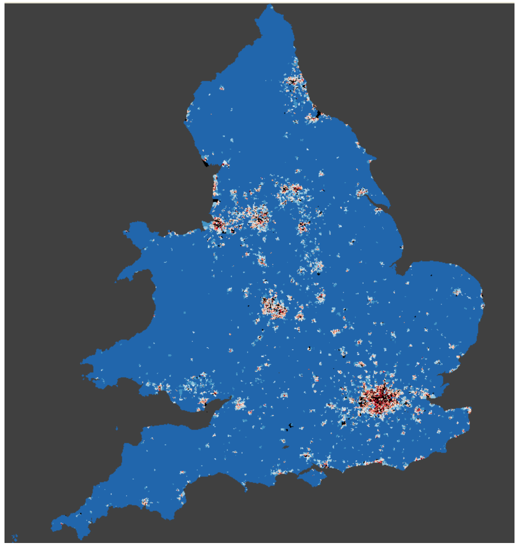
(b) 1st January 2011



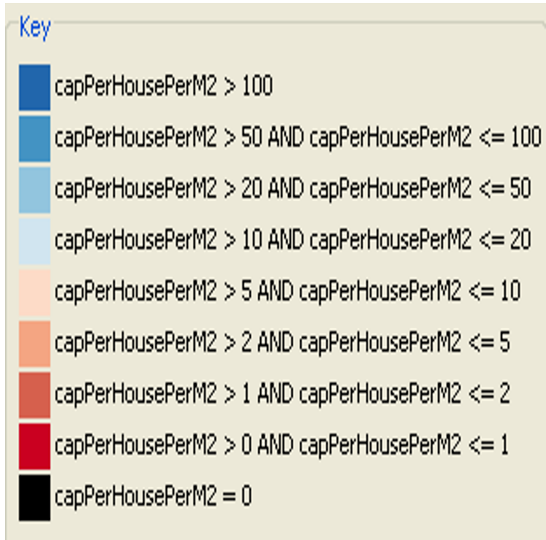
(c) 1st January 2012



(d) 1st January 2013



(e) 30th June 2013



(f) Key

Figure 7.15: Snapshots of capacity installed divided by household density per LLSOA. Each map is a snapshot in time

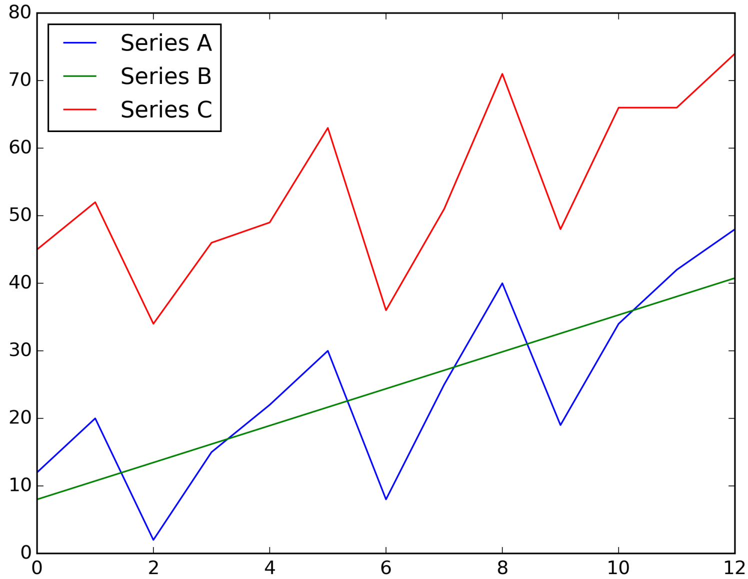


Figure 7.16: Timeseries' B & C are two possible models of timeseries A. In assessing the similarity to timeseries A, timeseries B would minimise the mean squared error (MSE) and therefore appear a *good* fit, whereas timeseries C, whilst being intuitively more similar, exhibits a high MSE. With OPA the situation is reversed

Source: after Thorngate and Edmonds (2013, , Figure 1, see that paper for further examples)

7.7.1 Ordinal Pattern Analysis

The technique used for evaluating the similarity between adoption patterns in different areas was Ordinal Pattern Analysis (OPA) as described by Thorngate and Edmonds (2013). In that paper, the authors recommend the technique as a method for comparing simulation and empirical data series, the technique can be applied more generally to make a statement about the qualitative similarity of two quantitative time series, as in this instance. OPA is based on the principle that what matters when matching longitudinal (timeseries) data is whether the *ordinal* rather than *cardinal* characteristics of the series are in some statistical sense similar.

To this end, OPA encodes a timeseries as a set of relations between points. If we denote a timeseries of length n as a set of readings D and say $d_i \exists D \forall 0 \leq i < n$, then OPA tests first whether $d_1 > d_0$, then whether $d_2 > d_1$ and $d_2 > d_0$ and so on to d_{n-1}. This gives a set of $\frac{n \cdot (n-1)}{2}$ ordered pairs which encode the shape of D.

Two timeseries can then be compared based on the proportion of these ordered pairs match - simply define k_{match} to be the pairs matched, $k_{mismatch}$ to be the pairs mismatched and the metric is $\frac{k_{match}}{k_{mismatch}+k_{match}}$. This is called the probability of match and denoted PM. The index of fit (IOF) is defined to be $PM - (1 - PM)$ which is the same as $2PM - 1$ and has the happy characteristic of providing a scale where $IOF = +1$ means all pairs match, $IOF = 0$ means half the pairs match and $IOF = -1$ means none of the pairs match.

Using this method, timeseries that have the same "shape", but differ in magnitude have the same encoding and will result in $IOF = +1$. If timeseries are stretched or offset by a given time, the match will not be perfect, but it is likely that patterns which exhibit a *similar* shape will have a *similar* encoding and thus have a high IOF. A bootstrapping method is used to quantify how likely it is that two OPA sequences are *similar*. This means that if OPA_{seqA} is being compared to OPA_{seqB}, the procedure is to find matching ordered pairs between OPA_{seqA} and OPA_{seqB} and then also with all permutations of OPA_{seqB}. The comparison metric is the fraction of the permutation matches which have more matches than the two non-permuted sequences. That fraction is denoted the Index of Fit (IOF). An implementation of OPA was written by the author in the Python programming language (C.1).

Results show that the majority of postcode areas have high OPA Indices of Fit (IOF) with a p value of less than 0.05 – a measure similar to the statistical p value giving an indication of the likelihood of the given correspondence being observed had the values been randomly ordered.

When performed at the LLSOA level, this analysis revealed that 21070 of the 31081 LLSOAs with any PV installed were similar to the overall trend with $p<0.05$. This means that $\sim$30% of the LLSOAs in the dataset do not conform to the pattern observed at the national level.

When performed at the PCD level, this analysis revealed that 2545 of the 2678 PCDs with any PV installed were similar to the overall trend with $p<0.05$. This means that only 5% of the LLSOAs in the dataset do not conform to the pattern observed at the national level.

Given these findings, the decision was taken to model at postcode scale (units of around 40,000 households), as this appears to give a scale at which results may be taken to be representative of the country as a whole. The implications of the model scale are explored further in the model results and discussion chapters (8 & 9)

7.8 Summary

Combination and analyses of the secondary data available to inform the model parameterisation for the study show the following results and implications for the modelling activity:

1. The introduction of the FiT triggered an increased rate of photovoltaic adoption, particularly domestic small scale PV. This reflects the economic incentive provided by this policy – it is clear that economic effects must be reflected in the model. However, incentive levels alone do not explain fully either the geographical or temporal distribution of adoption.

2. Typical domestic PV adopters install systems with a declared capacity of 4.0kWp or lower, with the most usual declared capacity being 4.0kWp. This indicates a strong effect of tariff banding on adopted capacity as the most favourable tariff applies only to installations of 4.0kWp or lower.

3. Changes to the tariff produce large spikes in the rate of adoption, with the effects of these transients being large enough to appreciably change the cumulative adoption curve (the S-curve)

4. The rate of adoption of domestic PV, after large acceleration, has returned to pre April 2011 levels and can be considered to be in a steady state of low adoption rate.

5. There is a geographical distribution of adoption with certain areas of the country showing stronger adoption than others – indicating that geographical conditions are an important factor.

6. The fact that significant numbers of timeseries at the LLSOA level differ in shape from the overall national time series (section 7.7) indicates that there is a local mechanism occurring within some LLSOAs and not others.

7. The drivers of differential rates of adoption within and between LLSOAs cannot be simply reduced to correlations between bulk demographic data and the bulk rate of adoption.

In light of the summary above, it is reasonable to conclude that the mechanism for adoption of PV is dependent on a complex interaction between adopters and their context, rather than a simple mapping from known gross variable (such as population density, or IMD, or economic incentives) and the adoption decision.

One factor which may be significant in domestic PV adoption is that they are highly visible and repeated observations of PV installations on others' dwellings may contribute to adoption of your own installation. The modelling work in this thesis (Chapter 8) investigates how such interactions, in combination with the other factors discussed, can contribute to the observed adoption patterns. This type of vicarious social learning is an effect which may be modelled in the Agent Based Model as described in Section 6.5.3 and may offer insight into the mechanism of technology adoption in the context of the electricity network and, more specifically, the future smart grid. It is notable that some other technologies often proposed as components of the smart grids (such as Electric Vehicles) are similarly visible to external observers, whereas others (such as smart controllers or heat pumps) are much less so, the importance of this for smart grid policy design is discussed in Chapter 9

The model parameters derived from this data analysis and taken forward into the modelling experiment described in the next chapter presented in Table 7.9.

Table 7.9: Model parameters derived from the empirical data analysis

Parameter	**Value or range**
Number of agents in simulation (N)	40420

Parameter	**Value or range**
Lead time for policy change to increase adoption rate (t_{lead})	4-6 weeks
Duration of peak due to policy change($t_{duration}$)	2 weeks
Household potential PV capacity (pv_cap)	2-4 kWp

Chapter 8

Model parameterisations and runs

In this section, the detailed experimental setup and results for a series of model runs are described. Section 8.1 describes the model context setup, which was the same for all the experiments reported upon. Section 8.2 describes agent setup, highlighting the parameters that remained constant between model runs and those that were varied. Section 8.3 describes the results of the ensemble of model runs undertaken. In section 8.3.3, simulation results are presented in the context of data on adoption in the case study area obtained from the data analysed in Chapter 7

8.1 Experimental context design

8.1.1 Geographical placement of houses

The model was configured to place agents in a realistic geography with one agent per a domestic dwelling in the LE2 postcode area, a largely suburban, residential postcode district. The choice of LE2 is arbitrary, but convenient as the author lives within it and usefully representative as it is a member of the set of postcode areas that have an essentially similar adoption pattern to the national one (see Chapter 7). The GIS data describing the position of buildings were obtained in the form of a polygon shapefile from the Ordnance Survey. The criterion for labelling a building likely to be domestic dwellings was having a footprint area between $30m^2$ and $160m^2$. 40420[1] buildings were identified as likely to be domestic dwellings; according to census data these house a population of 106,121

The position of LE2 in the country (Figure 8.1 & 8.2) and the buildings within LE2 (Figure 8.3) are illustrated. A realistic geographical arrangement was used to give a realistic spread of house-

[1] There are 45,245 address points in the LE2 PCD at the time of analysis. Of these, a small number are businesses. The 40420 estimate is arrived at using the process described.

hold positions, taking account of road orientation etc. In this simulation, the main effects of this were on the potential for social learning by observation (i.e. agent proximity) and the structural factors of house suitability for technology adoption. This postcode area covers a land area of 40,277,716 m^2 ($\sim 40km^2$).

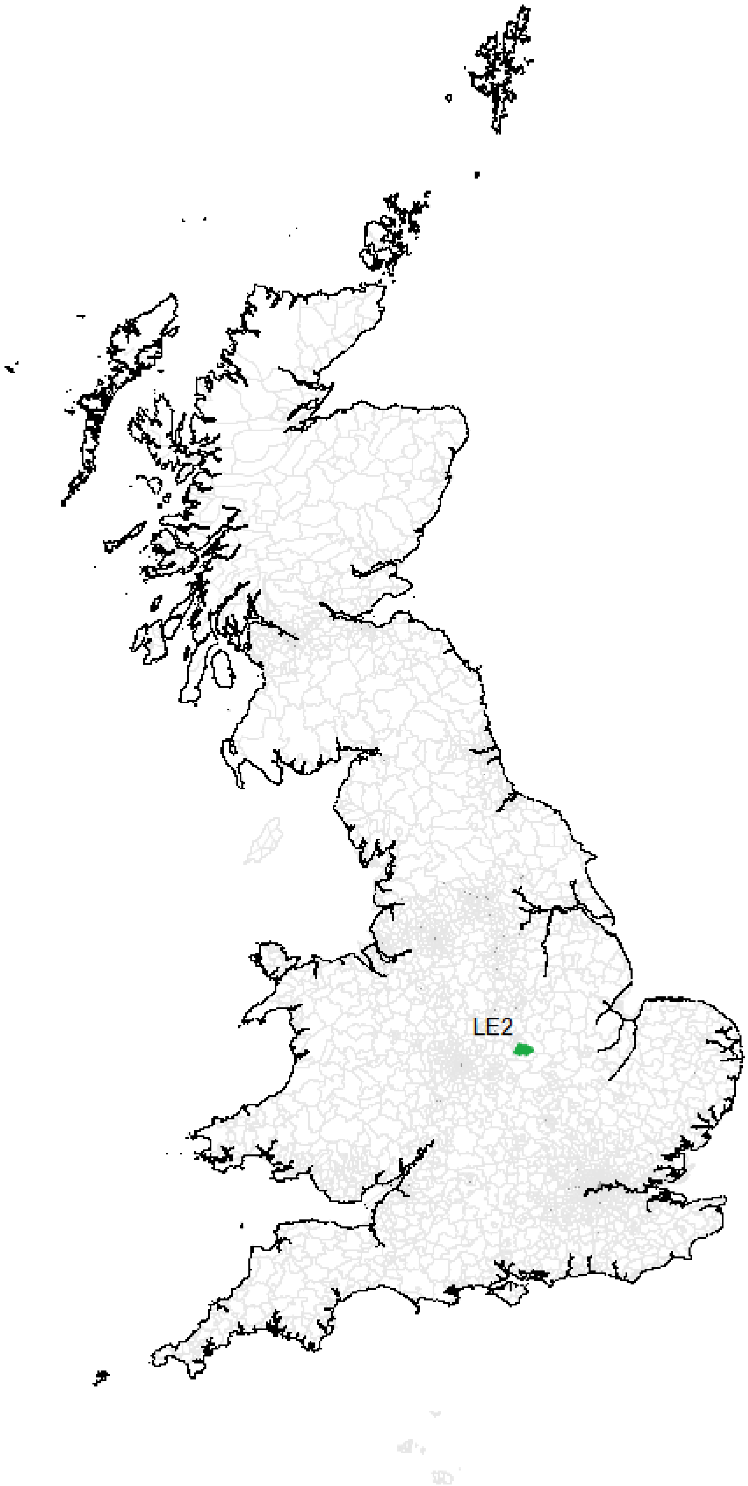


Figure 8.1: Illustration of position of LE2 postcode sector within the UK

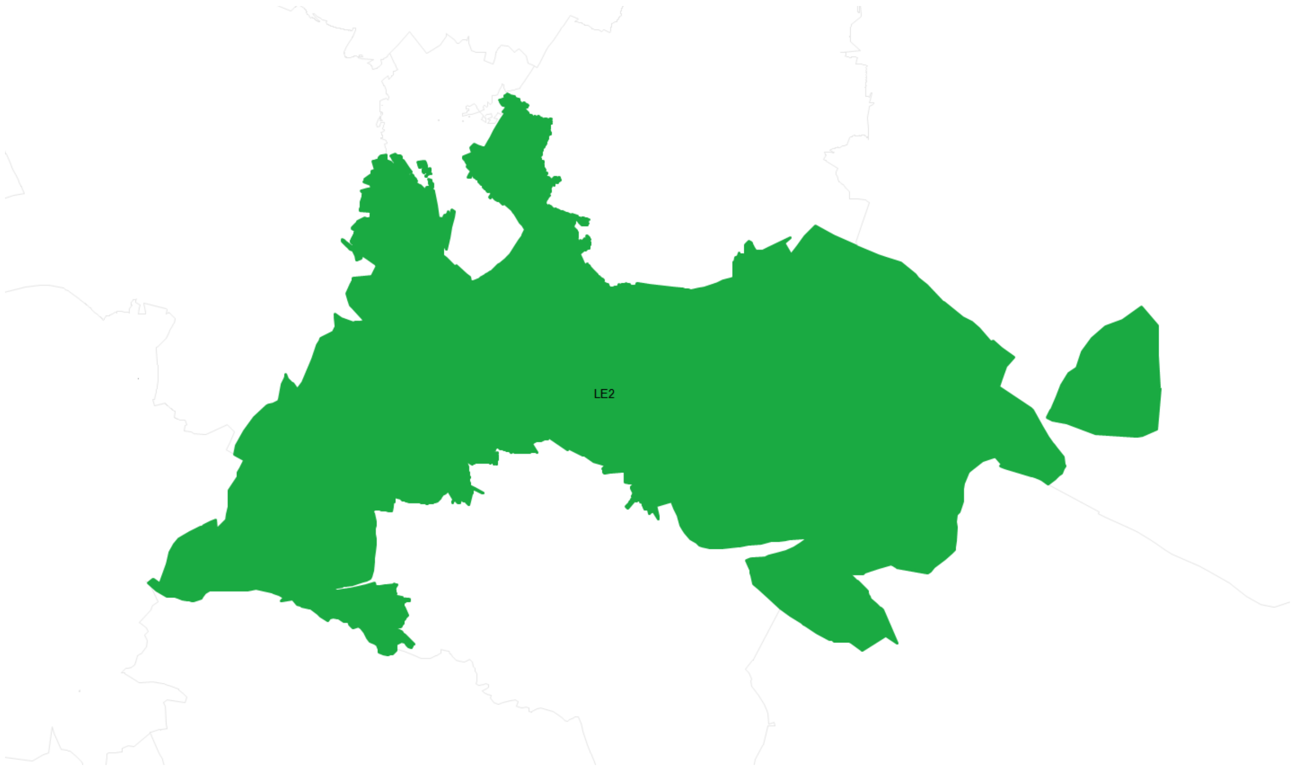


Figure 8.2: Diagram of LE2 area

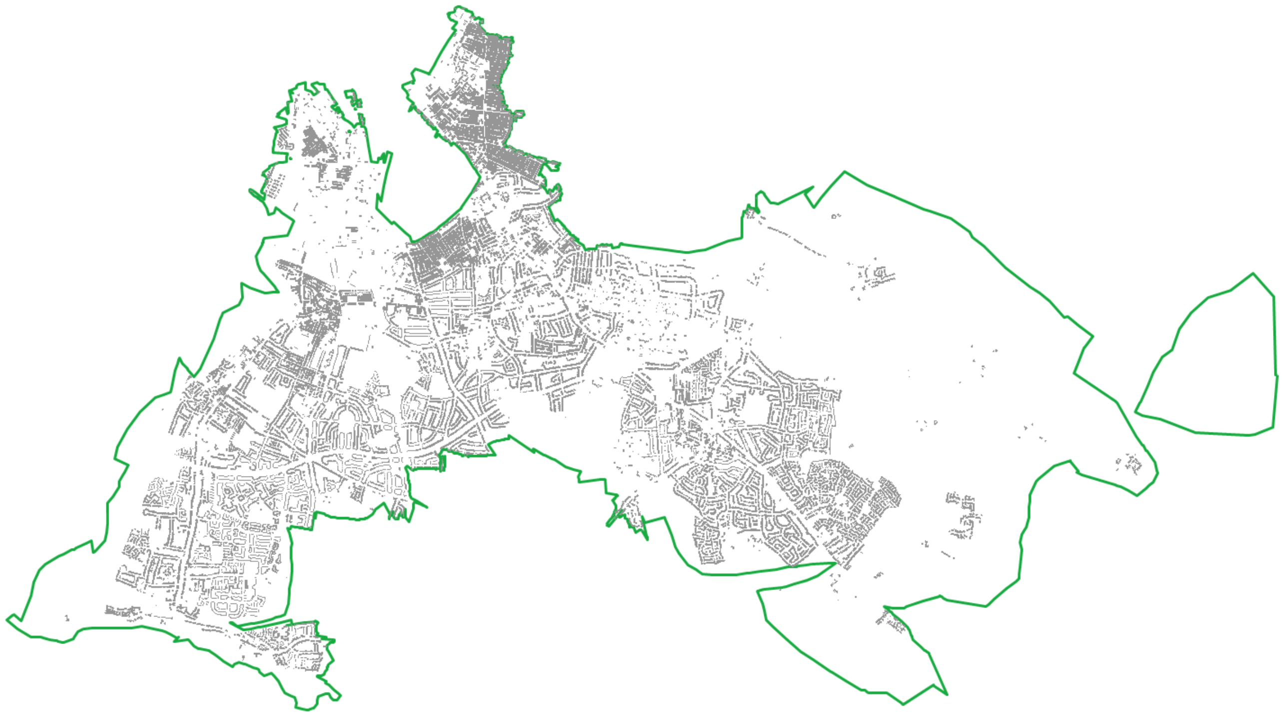


Figure 8.3: Domestic building layout in LE2 area

8.1.2 Price of investment

The price of investment for an agent is modelled as a random "on cost" to represent the profit of the installer (randomly selected between 5% and 20% as the agent gets a quote) plus a cost per unit size of the system, i.e. to install a PV system has a cost of installation plus a material cost per kWp installed. These prices are not fixed over time, but *are* the same for all household agents. This represents a simplification, as materials costs may vary, but this is not considered to be significant heterogeneity when researching the influence of householder behaviour on PV adoption.

8.1.3 Policy incentives

Every agent is able to query the policy incentives available for the adoption of technology; that is the level of FiT is available to each agent. The tariff bands and times of change within the simulation are as for the real-world changes in policy. The same information is available to all agents, although as described in section 6.5 (Figure 6.7), not all agents will query the information, or use the same frequency of querying, or have the same perception of when the incentives might change.

8.1.4 Weather

Temperature, wind speed and insolation were provided to household agents by means of a weather file. As agents were relatively localised, all agents were taken to receive the same weather. This is a modelling simplification made for this research undertaken, however the limitation is not believed to be significant due to the geographical boundaries of the simulation. The weather does not have a direct effect on the adoption process, but does affect the demand calculated for the households in aggregate during the simulation.

8.1.5 The electrical grid

The agents are taken to be connected to an electricity network of infinite capacity so that, within the model, they do not experience black- or brown-outs due to excess demand on the system, nor are they prevented from adopting PV due to network capacity constraints. However, overall demand on the system and particularly localised instances of high demand are recorded over the simulation and potential grid implications are discussed in chapter 9.

8.2 Experimental design

8.2.1 Initial configuration

Each agent was assigned a pro-environmental category based upon a draw from a random distribution configured to match empirical distribution found in the DEFRA categorisation (DEFRA, 2008). The seed for the random number generator used determines the initial configuration of pro-environmental category (and associated pre-dispositions). A sample configuration for a small area of LE2 is shown in Figure 8.4

8.2.2 Model parameterisation

According to the pro-environmental category assigned to model agents, they were parameterised with an economic ability and propensity to install as per table 8.1. Propensity to install is scaled such that a Positive Green with no other incentives might adopt microgeneration at roughly the rate observed before the FiT incentive. Relative weights are based on the author's interpretation of qualitative statements about relative attitudes to installation contained within DEFRA (2008).

Table 8.1: Mapping pro-environmental category to numerical representation of ability and propensity to install

DEFRA pro-environmental behaviour category	Economic ability to install	Propensity to install microgeneration
1 : Positive Greens	1	0.001
2 : Waste watchers	0.75	0.0005
3 : Concerned consumers	0.75	0.0005
4 : Sideline supporters	0.2	0.0002
5 : Cautious participants	0.5	0.00025

DEFRA pro-environmental behaviour category	Economic ability to install	Propensity to install microgeneration
6 : Stalled starters	0.2	0.000025
7 : Honestly disengaged	0.2*	0.0000025

A small number ($\sim$0.05%) of initial adopters of PV were assigned of the population based on the number of pre-existing adoptees observed in the data for the LE2 postcode district (14 of 40420 households). The exact households seeded as initial adopters were assigned based upon a number drawn from a uniform random distribution exceeded a threshold based on the agent's propensity to adopt.

Figure 8.4: Small section of LE2 buildings showing a sample of DEFRA pro-environmental category assignment for random seed 1. The exact configuration for each run depends on random seed

8.2.3 Results Analysis method

The ABM developed as part of this study is a stochastic tool. As the system being simulated is complex, it is likely that the simulation will be sensitive to initial conditions. It is therefore important to ensure that the system behaviour observed in each run is understood and analysed in the context of all possible runs of the simulation. Practically, it is not possible to test every possible run of the simulations, however a number of model runs with different random seeds can be performed. The larger the number of runs, the more chance there is that a representative sample of system behaviours will be seen within the result set. These effects are discussed in more detail in section 8.2.4

8.2.3.1 Spaghetti plots

Even a small number of parameter combinations can require a large number of model runs to give useful results (see section 8.2.4). Visualising and interpreting the rich dataset provided by such multiple runs is itself a challenge. Spaghetti plots have been adopted for that purpose in this thesis. In these plots, each run is plotted as a single line on axes of number of adoptions against time. Each line has a high transparency, but the plot is such that as multiple lines overlay upon each other, the opacity adds, such that the colour appears darker. These lines are plotted for all runs with a given parameter combination. In this way the trajectory of each model run per timestep is visible and the concentration of runs around certain states is conveyed by the intensity of the colour. The code to produce these plots was written by the author in the R and Python languages.

As noted in the introduction to section 6, it is important to also analyse the results of the simulations qualitatively. Analysing result sets purely in terms of means and standard deviations, regressions and measures of fit is likely to lose some of the insight offered by ABM simulation. The path taken to reach an end state of the simulation contains, generally, more information than the end state itself. In addition, the outlying states may offer more information about unusual and interesting operating modes of the system than the many states clustered around the operation of the system that is in some sense normal. The same is true of the time-series of various measures through the run of the simulation, which define the path to the simulation end state. Whilst the distributions of end states over many runs and the distribution of paths to those end states offers useful insights into operating modes of the system, the most telling insight comes from the qualitative analysis of paths and end states – in particular the outliers and counter-intuitive results.

Spaghetti plots facilitate this sort of analysis, as they quickly highlight outlying paths as well as outlying start or end states, for instance paths that experience a surge in adoption early or late in the simulation compared to others, or paths that have multiple surges of similar magnitude as opposed to a single surge.

8.2.4 How many runs?

As the implemented model is stochastic, it is important to decide how many runs of the model with different random seeds is necessary to give useful results with a given parameter combination. This was tested with a simple model where adoption was based on neighbourhood observation, where the observation radius of each agent was drawn from N(10,5).

Initially, 10 runs of each combination were undertaken, with the random number generator seed changed each time. Checks were performed to ensure that runs with the same random number seed resulted in the same output in order to ensure reproducibility.

Initial runs indicated that interesting distributions of final state and pathways to that state were emerging (Figures 8.5 & 8.6). In order to test the robustness of these results, a further run with 50 random seeds was conducted, which appeared to indicate that a bimodal distribution of final states may be emerging (Figures 8.7 & 8.8). However, a further run of 200 random seeds per parameter combination (11,000 runs in all – taking around 24 hours elapsed time with this fairly simple configuration) indicated that the distribution of final states, whilst not simply normal, appeared not to be bimodal (Figures 8.9 & 8.10).

Figure 8.5: 10 runs of simulation model with % adoption

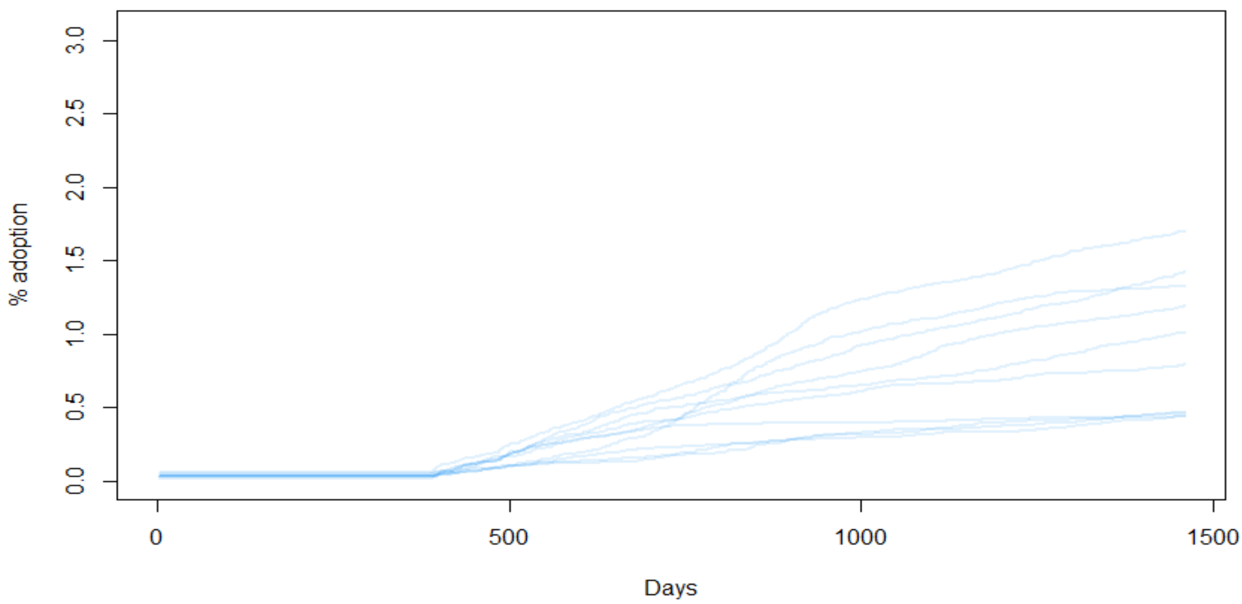


Figure 8.6: Histogram of end states after 10 runs (% adoption)

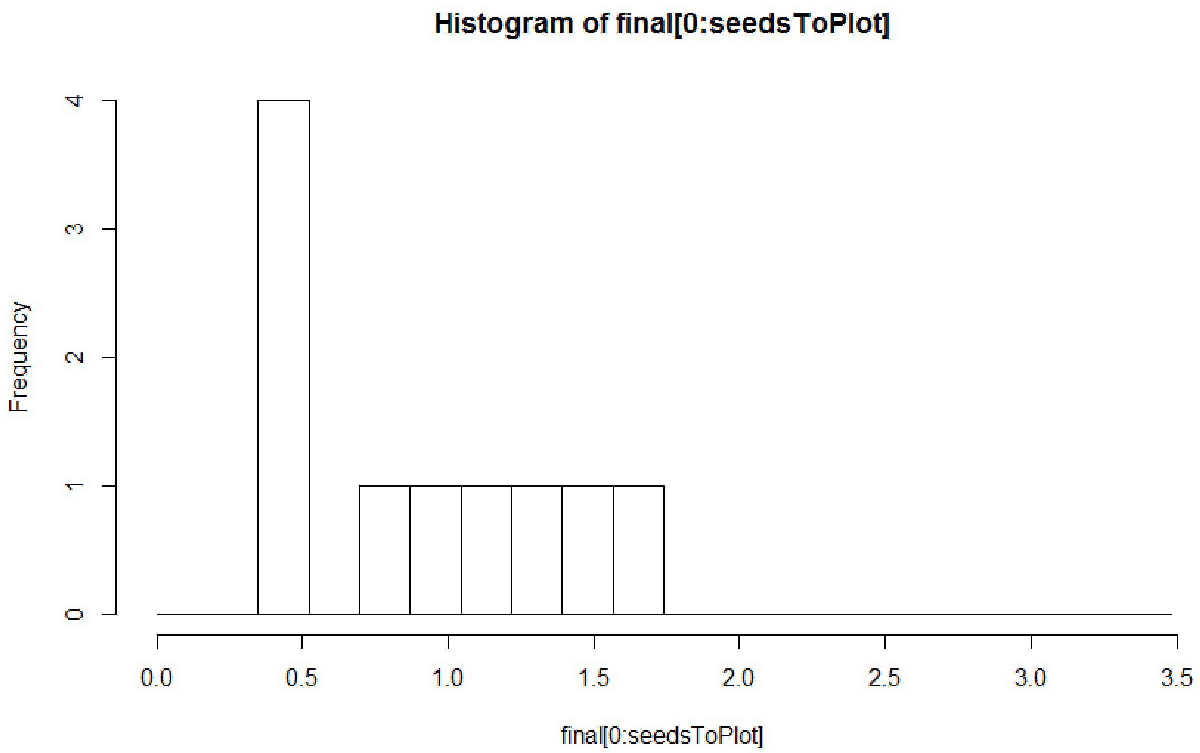


Figure 8.7: 50 runs of simulation model with % adoption

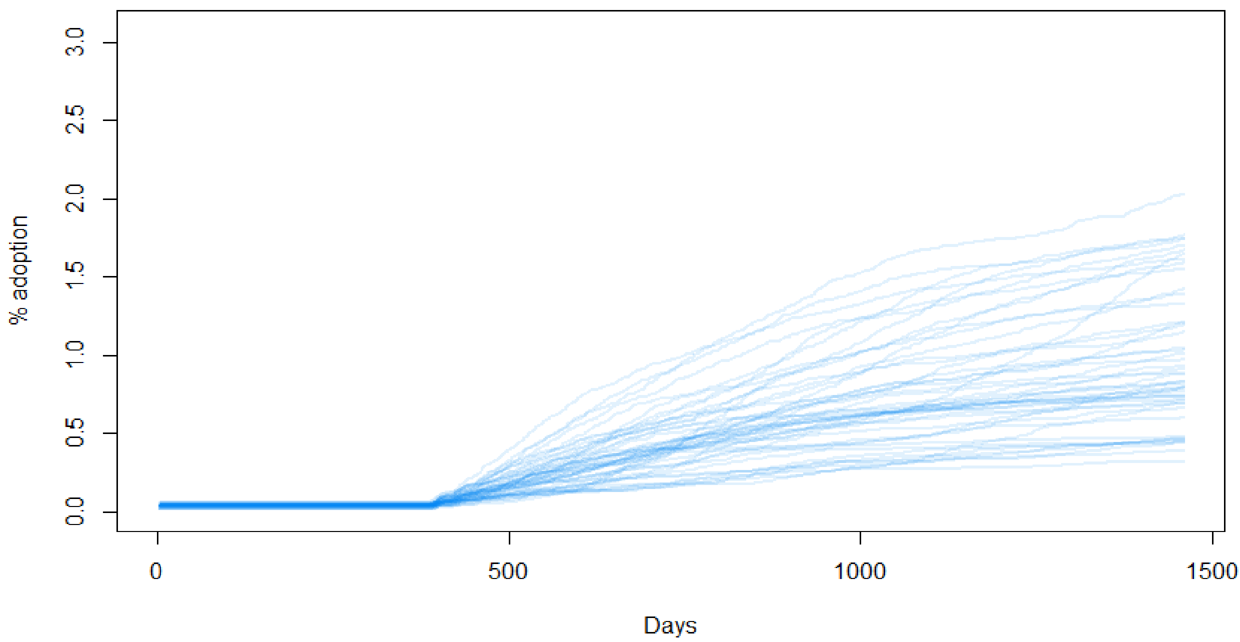


Figure 8.8: Histogram of end states after 50 runs

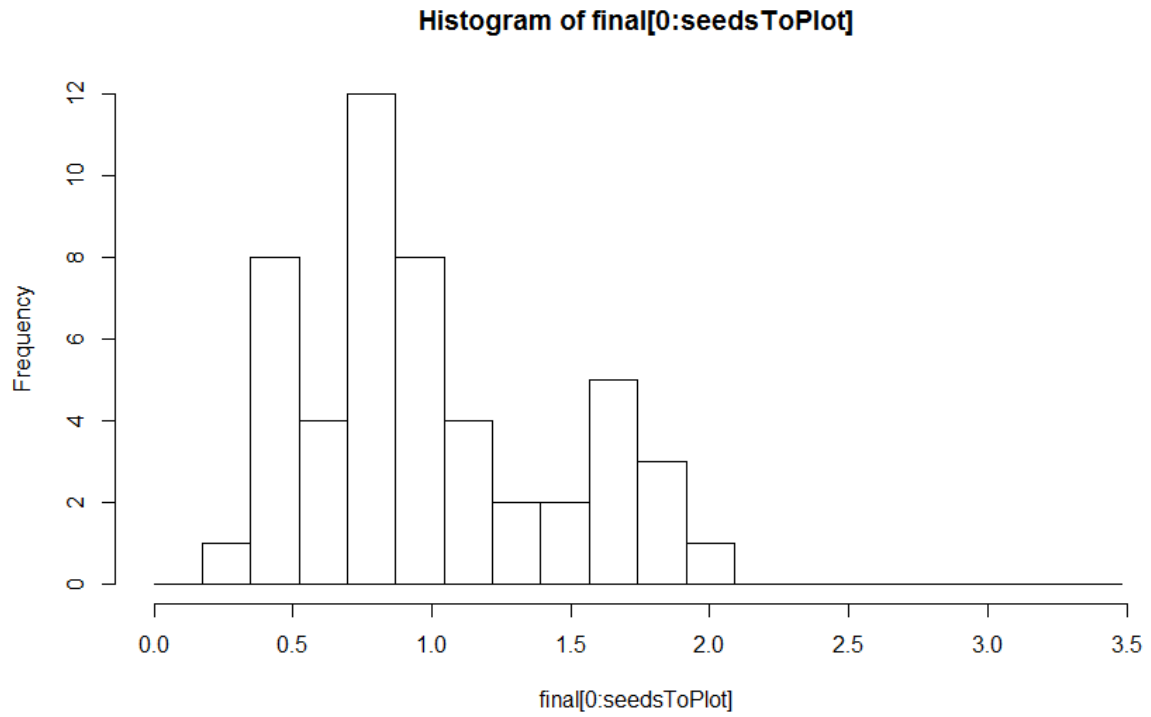


Figure 8.9: 200 simulation runs outcome of % adoption

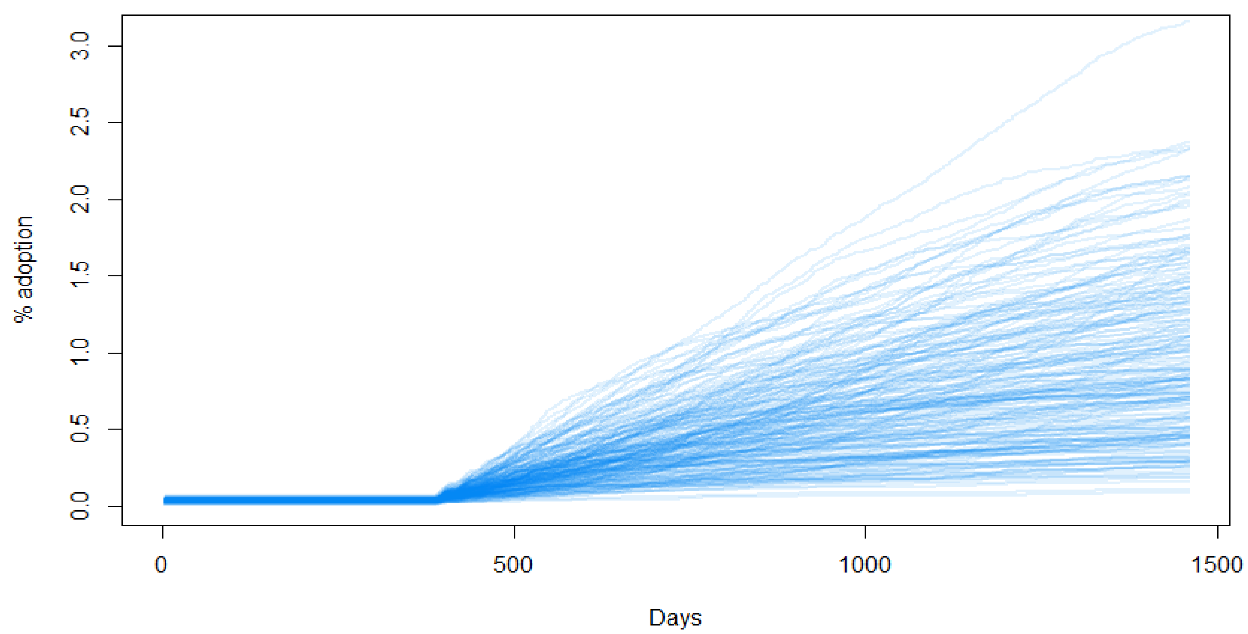
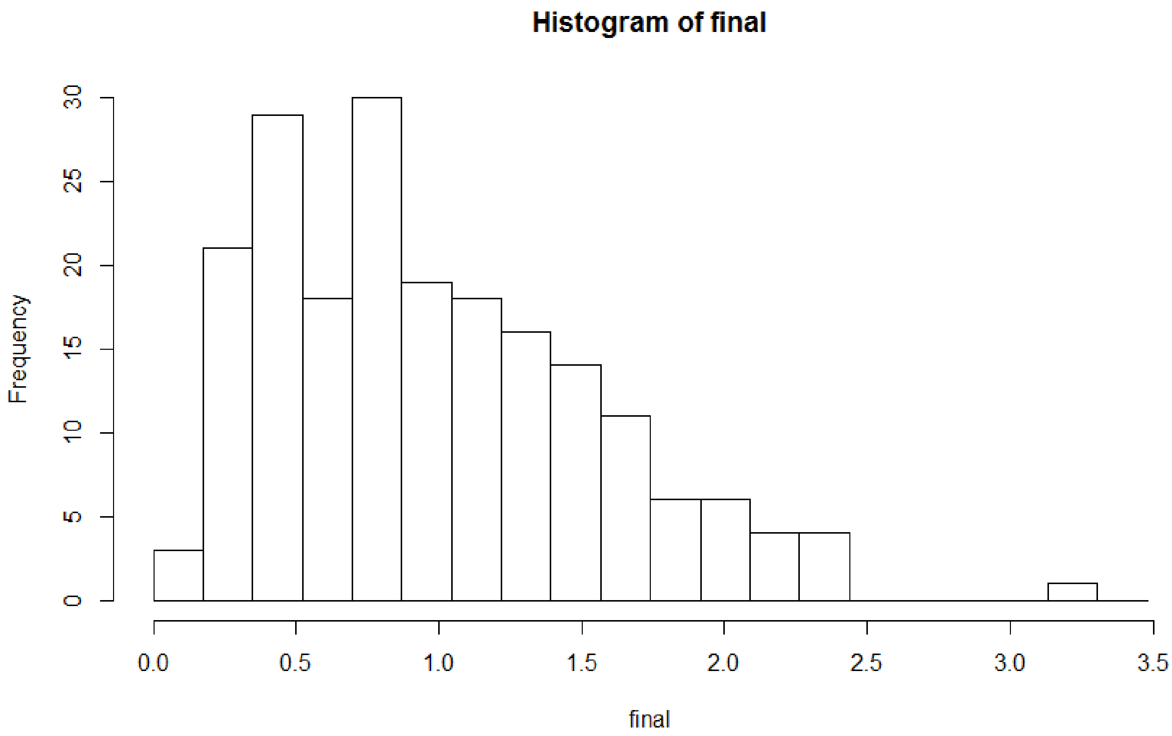
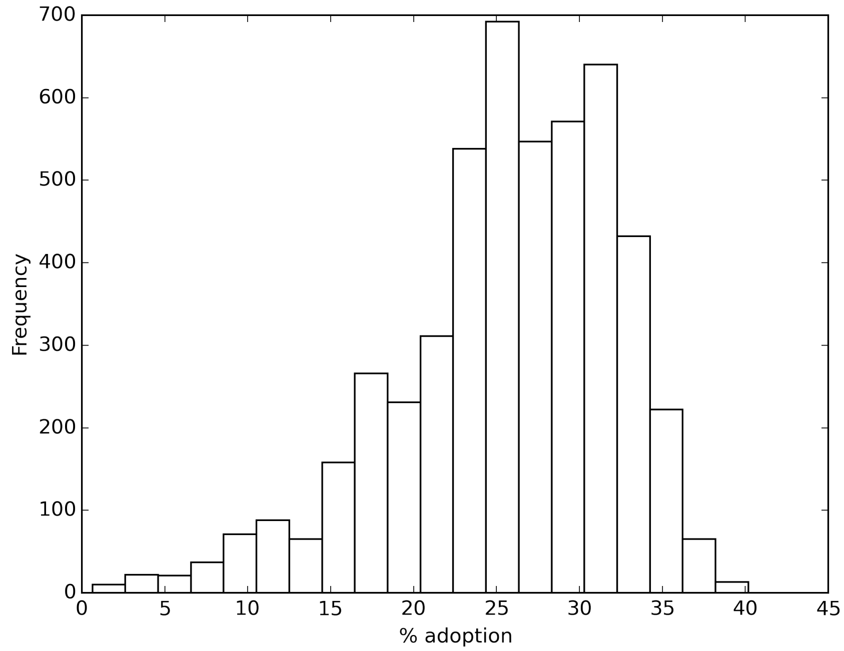


Figure 8.10: Histogram of end states after 200 runs (% adoption)

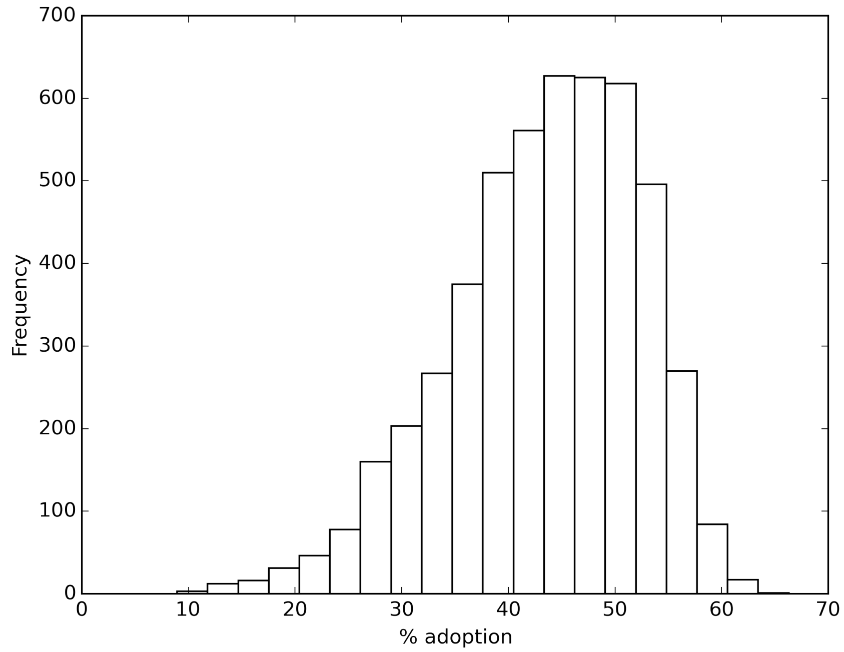


8.2.4.1 Very large runs

Finally, a run with 5000 random seeds was performed for each of two particular combinations – in particular μ=25 and $\sigma^2 \in \{0, 10\}$, with the financial incentive set extremely high to encourage as much adoption as possible in the simulation. The results of these, (Figure 8.11), appear to confirm the result for 200 runs, that the distribution is a skewed Gamma-like distribution, rather than bi-modal. The interesting features to examine are the mean, variance and skew of the output distributions.



(a) Distribution of end states for 5000 runs with observation radius $\sim$N(25,0)



(b) Distribution of end states for 5000 runs with observation radius $\sim$N(25,10)

Figure 8.11: End of pathway distributions for 5000 runs of simulation with high financial incentivisation and μ=25 and $\sigma^2 \in \{0, 10\}$

As a consequence of these runs and results, further model runs use 200 runs for initial analysis, with larger runs performed if the distribution at a particular timestep is to be used to make strong conclusions.

8.3 Experimental results

This section describes three sets of experiments conducted using the model to investigate observed features of the adoption data under the FiT.

8.3.1 Modelling of external shocks

An initial set of experiments was performed with an early version of the model to verify the ability to model the shocks engendered by policy change. This set of experiments investigated modelling agents' perception of the urgency of decision making, in order to allow for the model to simulate rapid adoption over very short timescales observed in the real data as spikes in adoption rate (Chapter 7). Thus, the model was set up with to include the perception of imminent change to tariff as an influence to adoption. The variable controlling this within the household agent was named decision_urgency.

$$\frac{\beta}{d-t} \tag{8.1}$$

where

u_t is the urgency parameter at timestep t,

d is the announced date of the next tariff review and

β is a tunable parameter to modulate the rate of change of urgency with time.

In terms of the SCT model, this experiment had the following setup. Construct values were set as per table 8.2 and relationship weightings as per table 8.3.

w_{POE} was set to a low value to avoid observation effects swamping the effects of shocks in this scenario. w_{SSF} was not utilised in this experiment as socio-structural factors were pre-applied by configuring the `potentialPVcapacity` variable at initialisation.

Although the method of urgency calculation is the same for each agent, because the decision making process is triggered randomly in time throughout the population as previously described, there is heterogeneity within the population with regard to the value of c_{OE} at decision making time. With this model scenario, spikes in adoption due to perception of imminent change were

Table 8.2: Construct values

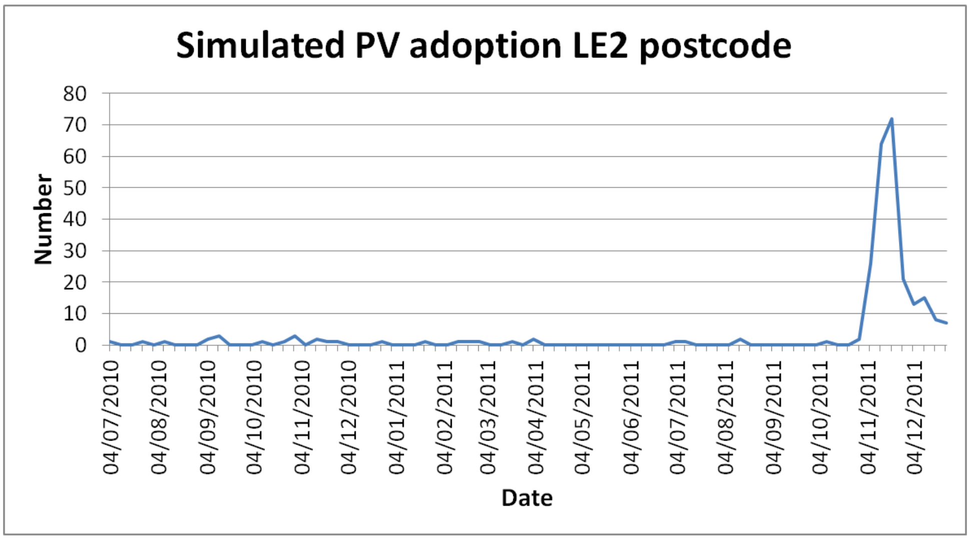
Construct	**Value**
c_{OE}	calculated within the model as `economic_sensitivity` (as per 8.1) multiplied by `tariff` (8.1.3) multiplied by u_t
c_{POE}	fraction of neighbours adopting (fixed radius of observation r, homogeneous across population)
c_{SE}	`microgenPropensity` as per 8.1 - heterogeneous across the population and randomly assigned in proportion to DEFRA (2008)
c_{SSF}	Not implemented in this scenario

Table 8.3: Relationship weights

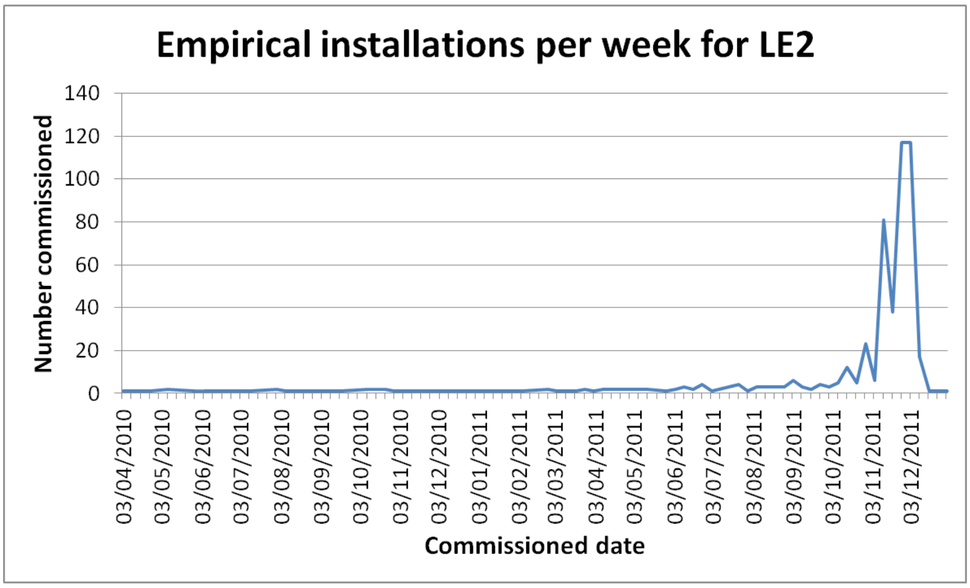
Weight	**Value**
w_{SE-G}	1
w_{OE-G}	1
w_{POE-G}	0.4
w_{G-B}	1
All other weights	0

possible. The results from this experiment were reported in Snape (2013) and are reproduced below with the relevant section of the observed adoption for comparison (Figures 8.12a & 8.12b). These results show the output for a single run of the ABM, presented to illustrate that the simulation results follow the pattern observed in real data showing that using an urgency variable within the agent in this way was useful.

Following this set of experiments, in accordance with the research workflow (Figure 6.1), the model design was re-evaluated and more weights and constructs were added to the model. During this evaluation phase, another similar methods for calculating this variable was implemented and tested (equation 8.2). In the results reported in this section, formulation 8.1 was used, how-



(a) Modelling spike in adoption using urgency as a component of outcome expectation (LE2 area)



(b) Observed spike in adoption due to policy announcement in late 2011 (LE2 are)

Figure 8.12: Simulated and empirical adoption rates to end of 2011 in LE2 area

ever the later full-featured models use formulation 8.2. This was adopted latterly simply in order to restrict the value range of u_t to the range 0-1, thus making the choice of constant easier.

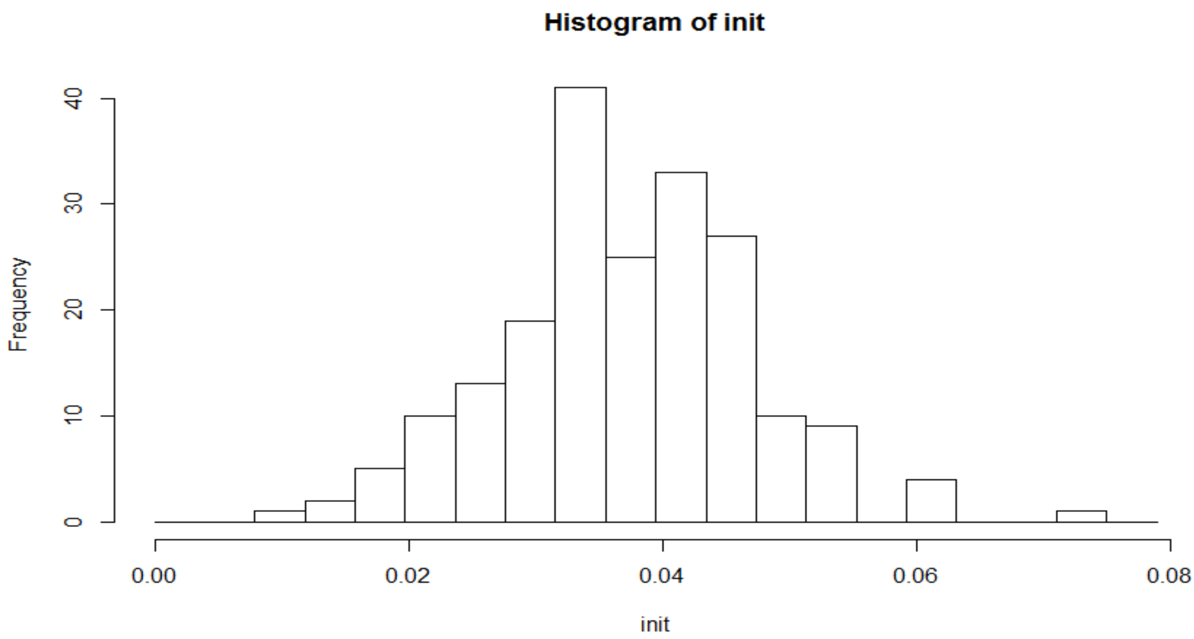
$$u_t = e^{-\frac{(d-t)}{\beta}} \tag{8.2}$$

β was set at 28, which means that urgency grew significantly for up to four weeks before any change of tariff.

8.3.2 Effect of observation

Experiments were conducted to understand the influence of agents' perception of the popularity of installing PV on the rate of adoption. Again, the number of initial adoptees was determined randomly as per section 8.2.2. This is sensitive to the random number generator seed only – the resulting distribution of initial adoptees resembles a somewhat noisy normal distribution for the 200 initial states (Figure 8.13).

Figure 8.13: Histogram of initial adoption state (x axis is % of agents with PV at initalisation)



8.3.2.1 Observation effect parameterisation

The ensemble of experiments presented here was to test the effect of vicarious learning by observation - changing the value of construct c_{POE}. In the model this means changing the radius that each agent observes (r_i) in order to compute the value of the observed normality of owning PV. Variables subscripted i indicate the per agent value, variables with no subscript should be assumed to apply across the simulation. Other constructs and weights remained the same as for the previous experiment.

Two effects were tested for:

1. Effect of differing observation radius r where all agents have the same value of r i.e. $r_i = k \forall i$
2. Effect of heterogeneity in r. This was done by drawing r_i from $r \sim N(\mu, \sigma)$

In all, 55 parameter combinations of μ and σ were tested (Table 8.4), with 200 runs for each combination[2].

Table 8.4: Neighbourhood vicarious learning model parameter combinations

Test	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$
1. (11 combinations)	0 to 25 in 2.5 increments	0
2. (44 combinations)	0 to 25 in 2.5 increments	2.5-10 in 2.5 increments

8.3.2.2 Effect of observation radius absolute level

In this experiment, all parameters remained the same except the radius of observation that each household took into account when determining the perception of others' behaviour within the SCT model evaluation. The radius of observation is in non standard units, this is due to the natural units of the geographic projection underlying the simulation being 0.01745° at a latitude of 52° North. This is equivalent to 1 unit being roughly 1.2 km.

The distribution of initial adoptees at the start of the 200 runs was the same for each set of

[2] A batch environment was developed in order to run many combinations in parallel in a cluster computing environment. Initially, the environment was developed by the author. With the release of Repast Simphony 2.1, the Repast development team implemented a similar environment natively within Repast and this was adopted.

experiments. In this suite of experiments, no variation in observation range was allowed between agents, so all agents had exactly the same observation range.

200 runs were performed for each $r \in \{0, 2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20, 22.5, 25\}$

Obviously, for r = 0, the social influence is zero.

Interesting results are seen for r ∈ {20, 22.5, 25} (Figures 8.14,8.15 & 8.16). These results show that an increased radius of observation both increases the total level of adoption and widens the range of observed observation. Recalling that radius of observation here is a proxy for the real world observation and influence from social networks, this result implies that as more households are observed to have installed PV, not only does the total level of installation increase (at least until adoption is saturated), but also the possible pathways become more widely dispersed – i.e. the range of possible outcomes to the policy intervention is more spread. The first is as expected; the latter less so. This means that the more widely observable the technology is, the more unpredictable the outcome of the policy. In all scenarios, certain pathways remain at very low adoption percentages, even when median adoption rate is high (e.g. 20% adoption). The implication of this is that even with very attractive policies, there remains a risk that adoption will stay low for certain combinations of parameters.

Figure 8.14: Adoption with all agents observing a 20 unit radius

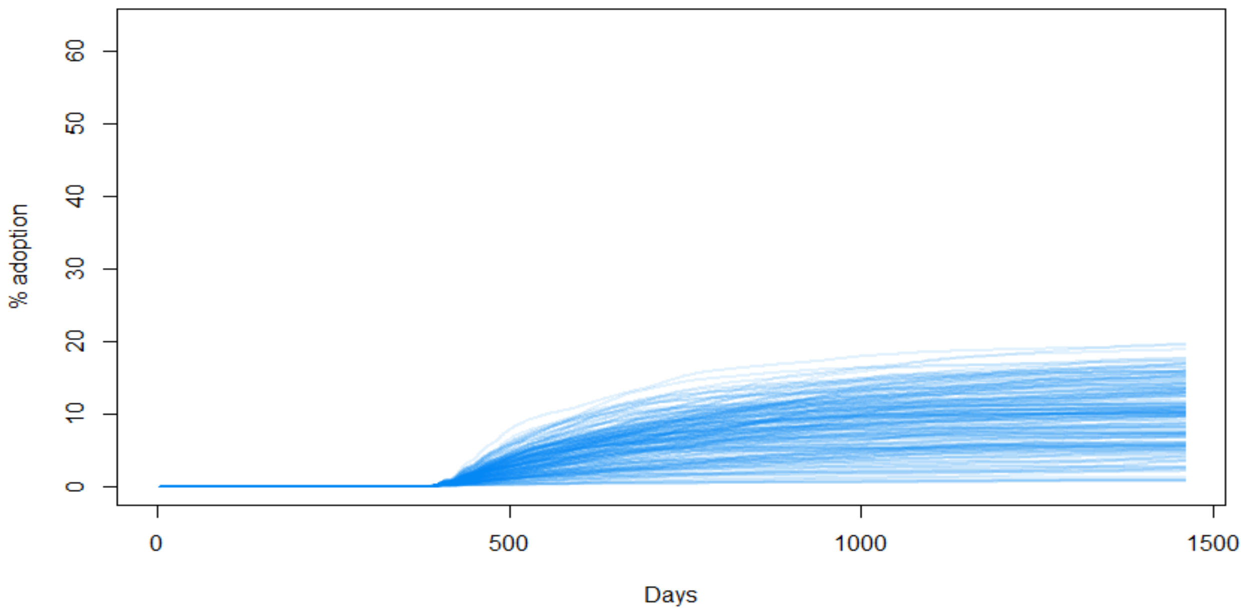


Figure 8.15: Adoption fraction with all agents having observation radius 22.5 units

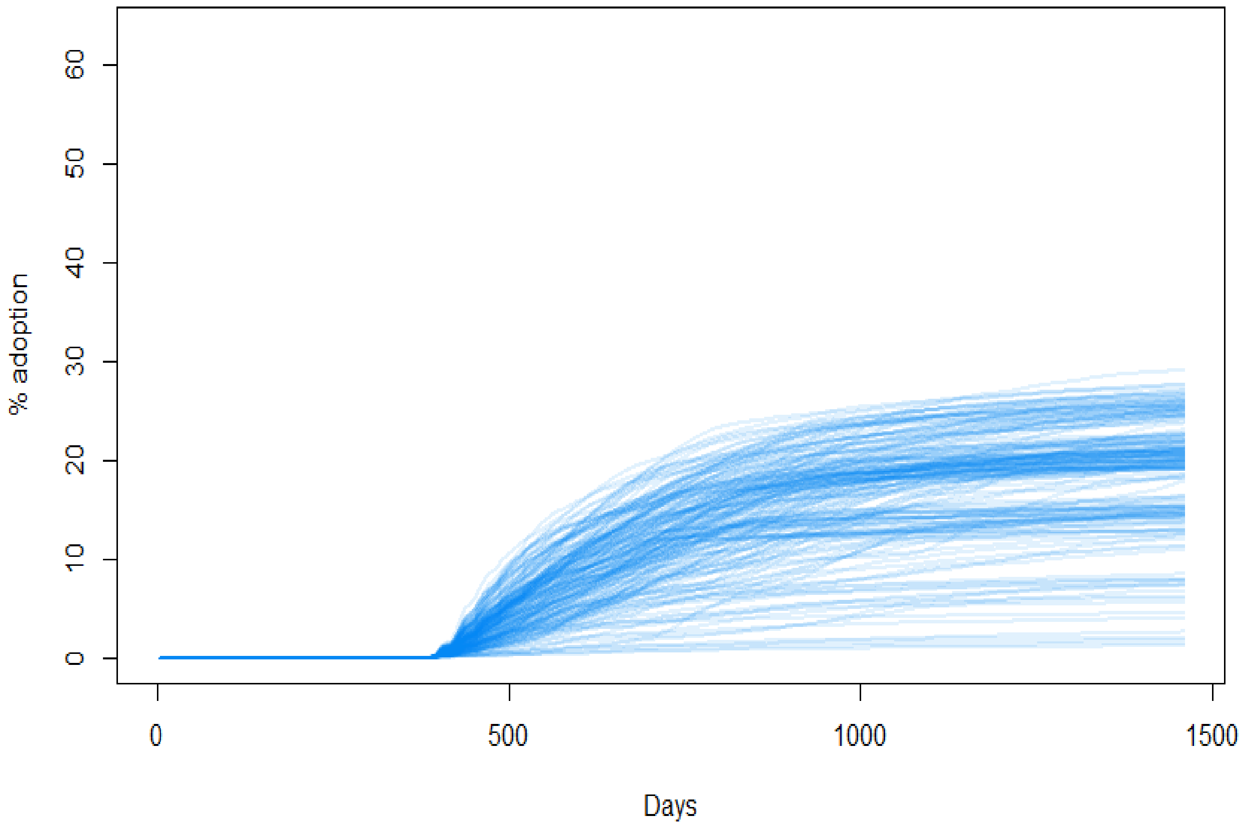
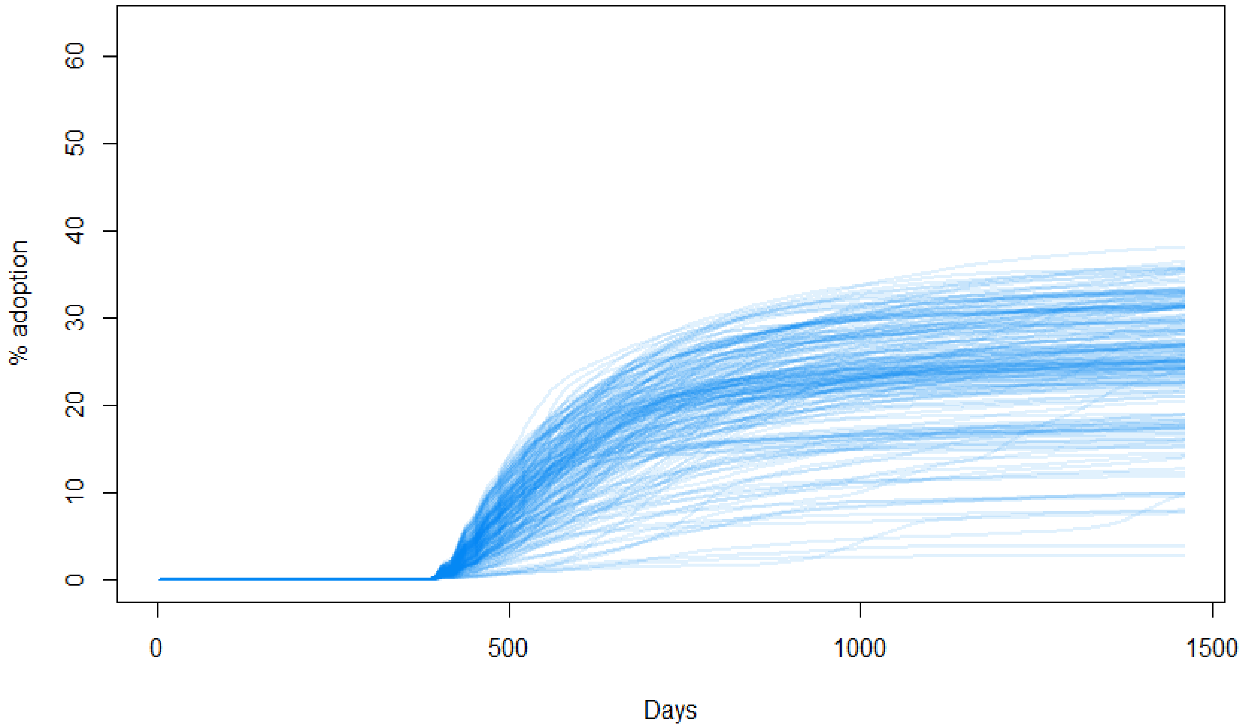


Figure 8.16: Adoption fraction with all agents having observation radius 25 units



8.3.2.3 Effect of observation radius heterogeneity

The next set of experiments was to investigate the effect of within-population heterogeneity of observation radius. The radii of section 8.3.2.2 were used as the mean of normal distributions from which the observation radii ri for each agent is drawn. The standard deviation of the distribution was varied as $\sigma \in \{0,2.5,5,7.5,10\}$. Obviously this gives the chance of some agents having negative radius – this is interpreted as zero. The heterogeneity has the effect of increasing the adoption percentage and the spread. Representative runs for $r \sim N(25, 0)$ and $r \sim N(25, 10)$ show this effect clearly (Figures 8.17 & 8.18).

Figure 8.17: Adoption percentage with homogeneous radius of observation amongst agents. Note - implemented by r N(25,0) - i.e. r = 25

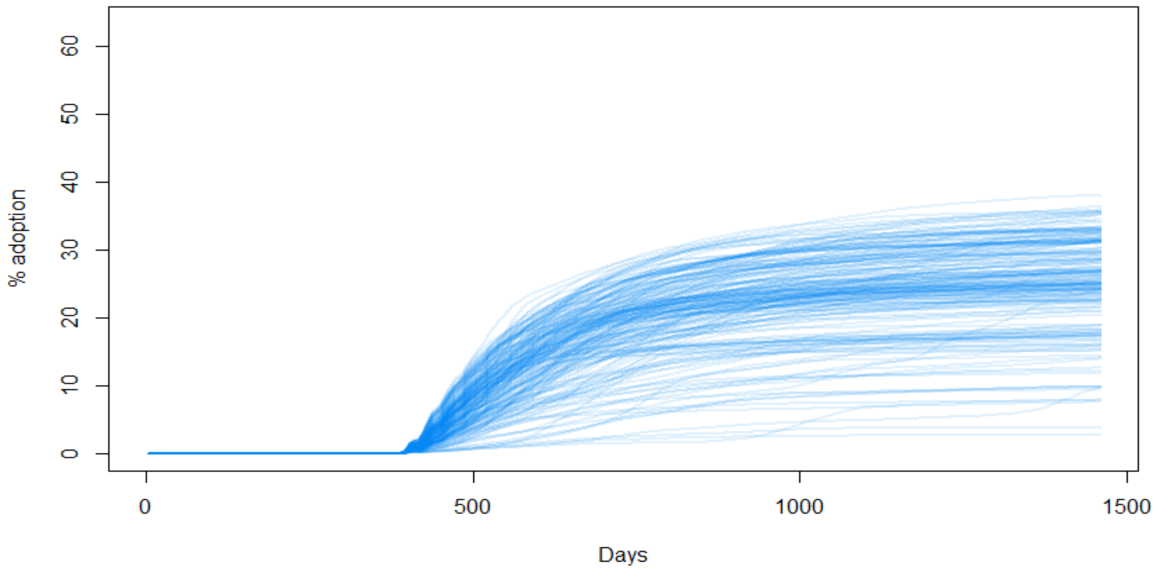
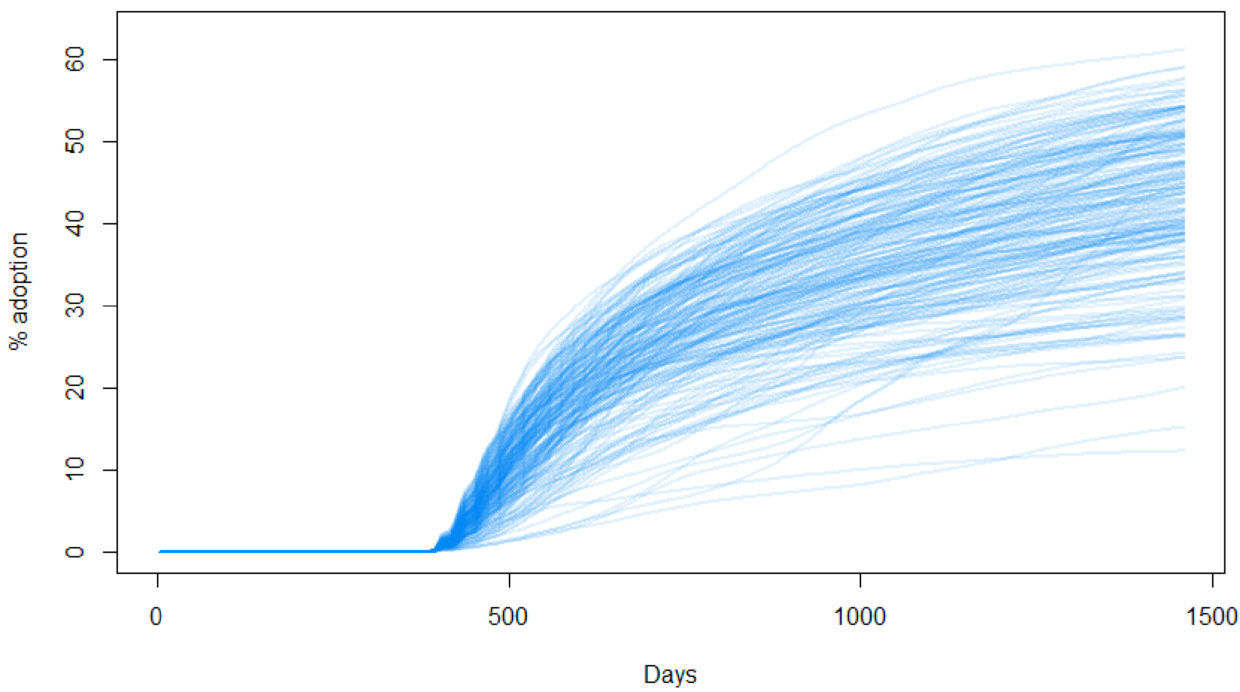


Figure 8.18: Adoption percentage with heterogeneous radius of observation amongst agents. Radii drawn from N(25,10) i.e. r˜N(25,10)



8.3.2.4 Summary of observation effect

The mean, standard deviation and skew of output distributions from each of the 55 observation radius parameter combinations is summarised in Table 8.5. All cells within the table are formatted with the mean at the top, standard deviation in the middle and skew at the bottom. The measure used for skew is the standard Fisher-pearson co-efficient. Values are rounded to 3 decimal places and describe the percentage adoption within the modelled population at the final simulation timestep.[3]

Table 8.5: Summary of pathway outcome distributions for all vicarious learning parameter combinations. Note all figures are percentage adoption (no units)

μ \ σ		**0**	**2.5**	**5**	**7.5**	**10**
0	Mean	0.037	0.043	0.056	0.074	0.11
	SD	0.01	0.012	0.017	0.024	0.044
	Skew	0.116	0.382	0.353	0.439	0.825
2.5	Mean	0.053	0.063	0.078	0.112	0.203
	SD	0.016	0.019	0.026	0.042	0.1
	Skew	0.445	0.431	0.624	0.666	1.246
5	Mean	0.111	0.117	0.134	0.217	0.502
	SD	0.037	0.043	0.05	0.103	0.3
	Skew	0.691	0.562	0.505	0.887	0.906
7.5	Mean	0.272	0.238	0.292	0.643	1.68
	SD	0.109	0.092	0.138	0.381	0.956
	Skew	0.541	0.442	0.925	0.818	0.428

[3]The code used to calculate these results from raw output files is available in appendix section C.2.

μ \ σ		**0**	**2.5**	**5**	**7.5**	**10**
10	Mean	0.427	0.477	0.98	2.408	4.677
	SD	0.164	0.207	0.564	1.34	2.279
	Skew	0.543	0.632	0.778	0.453	-0.058
12.5	Mean	0.654	1.137	3.379	6.495	9.568
	SD	0.261	0.625	1.751	3.094	3.823
	Skew	0.674	0.668	0.239	-0.107	-0.676
15	Mean	1.684	3.583	8.191	12.197	14.422
	SD	0.842	1.901	3.703	4.802	4.869
	Skew	0.644	0.506	-0.138	-0.689	-0.893
17.5	Mean	3.925	8.21	14.478	17.616	19.518
	SD	1.987	3.78	5.441	5.568	5.58
	Skew	0.468	0.015	-0.701	-0.968	-0.828
20	Mean	9.881	15.752	20.121	23.001	25.678
	SD	4.374	5.987	5.996	6.258	6.73
	Skew	-0.063	-0.566	-0.903	-0.833	-0.701
22.5	Mean	18.76	22.183	25.885	29.479	33.634
	SD	5.98	6.492	6.796	7.585	7.78
	Skew	-0.903	-0.914	-0.762	-0.621	-0.663

μ \ σ		**0**	**2.5**	**5**	**7.5**	**10**
25	Mean	25.229	28.709	33.06	38.325	43.014
	SD	6.966	7.449	8.14	8.883	9.068
	Skew	-0.772	-0.719	-0.685	-0.603	-0.573

As might be expected, the average radius of observation was positively correlated with the number of PV systems adopted. This can be intuitively explained by the fact that the wider the radius of observation, the more other households are observed and therefore the greater the chance that at least one will have installed PV. Quantitatively the effect is pronounced.

The effect of radius heterogeneity is more unexpected - with a heterogeneous mix of observation, the absolute level of adoption is increased, as well as the spread of pathways observed as measured by the standard deviation of the final distribution. The skew of the distribution also changes with the average adoption, simulation runs with low average adoption (top left of Table 8.5) have a rightward skew (i.e. a long rightward tail), whereas those with very high average adoption (bottom right of Table 8.5) show a leftward skew. This indicates that even in scenarios where observation is such that a high average adoption is likely, there remain simulation pathways that exhibit low percentage of adoption.

8.3.3 Modelled adoption rate compared to observed data

The above experiments indicate that an observation radius drawn from N(10,7.5) would most closely match real world deployment. The spaghetti plot for the full ensemble is shown below (Figure 8.19) as well as the distribution of end states (Figure 8.20). The x axis scale has been translated from days elapsed to dates to ease comparison with real world data.

One strength of the ABM technique is that having identified interesting parameter combinations, it is possible to interrogate data for individual runs within the ensemble. In this dataset, the run for random seed 45 is interesting as it shows a somewhat similar pattern to the real world data, albeit with the reaction to the policy shock being anticipated somewhat in comparison to real world results, making the spike much more spread, but somewhat lower in amplitude.

This suggests that the model can capture the real world effects observed, although it still

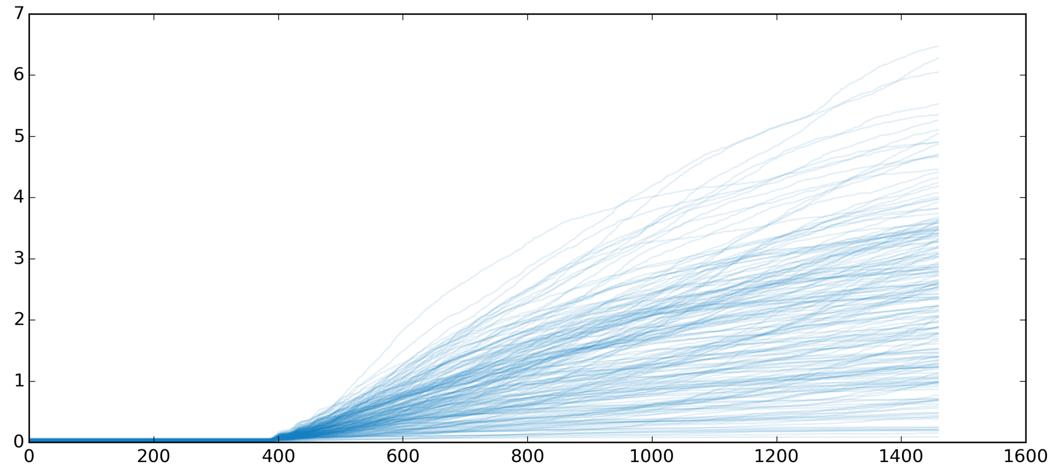


Figure 8.19: Spaghetti plot for $r \sim N(10, 7.5)$

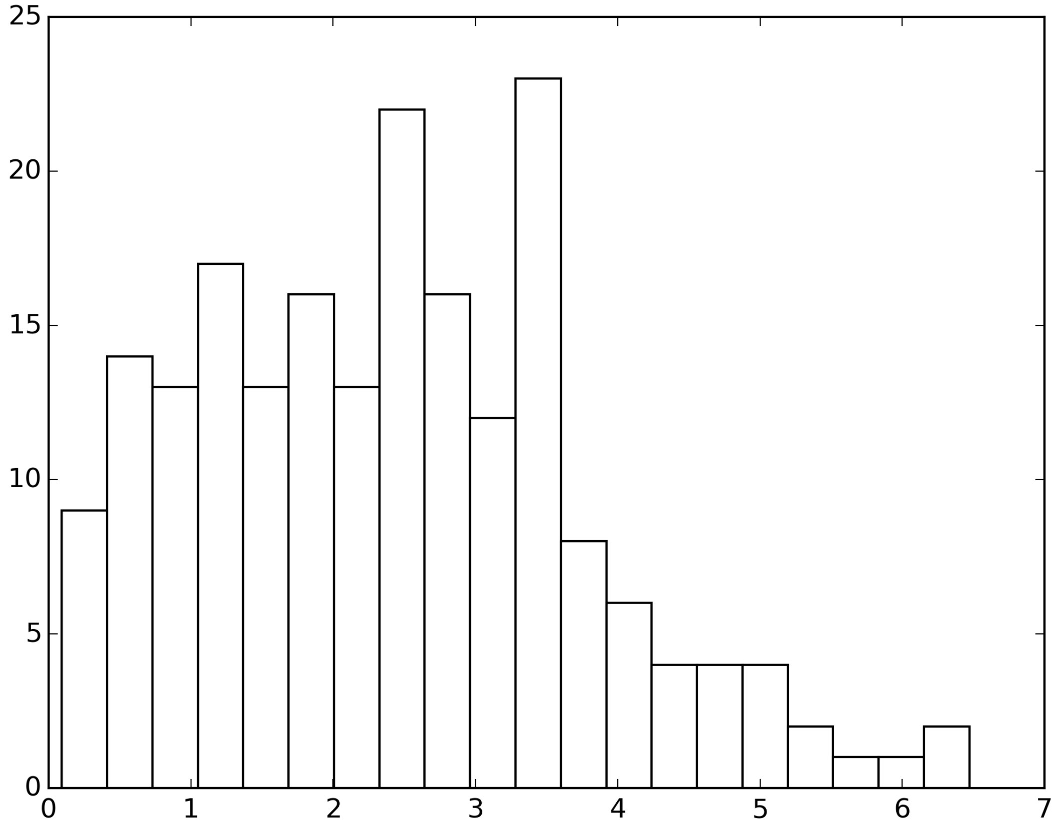


Figure 8.20: Histogram of end states for $r \sim N(10, 7.5)$

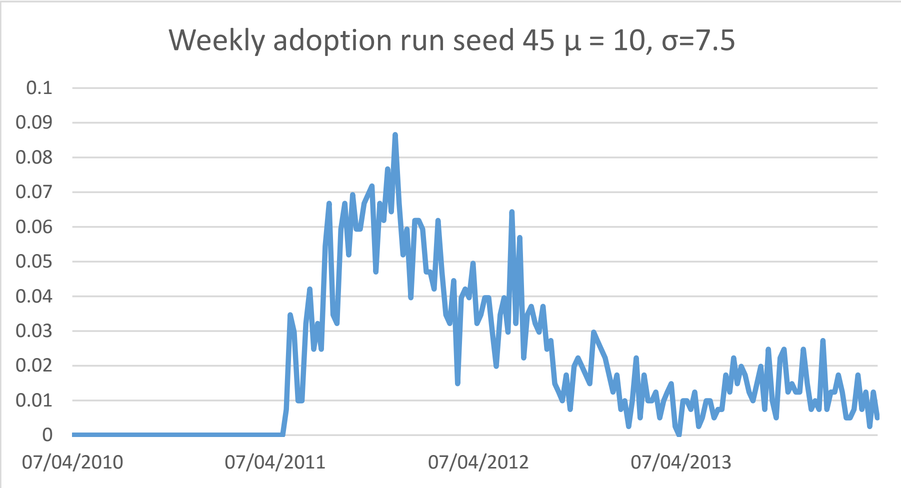


Figure 8.21: Illustrative pathway from a particular output (seed 45 from ensemble $r \sim N(10, 7.5)$)

smooths the very strong shock experienced with the first policy change. This parameterisation offers the best fit to the observed data. It is notable that adoption continues after the cuts observed, just as seen in real world data.

The observed rate of adoption in LE2 (up to June 2013) is shown in Figure 8.22. This shows a peak rate (adoptions per week) of 124 adoptions in the week commencing 3rd December 2011. The cumulative adoption curve (Figure 8.23) shows that there were 851 installs as of June 2013, representing 2.1% of the 40420 households.

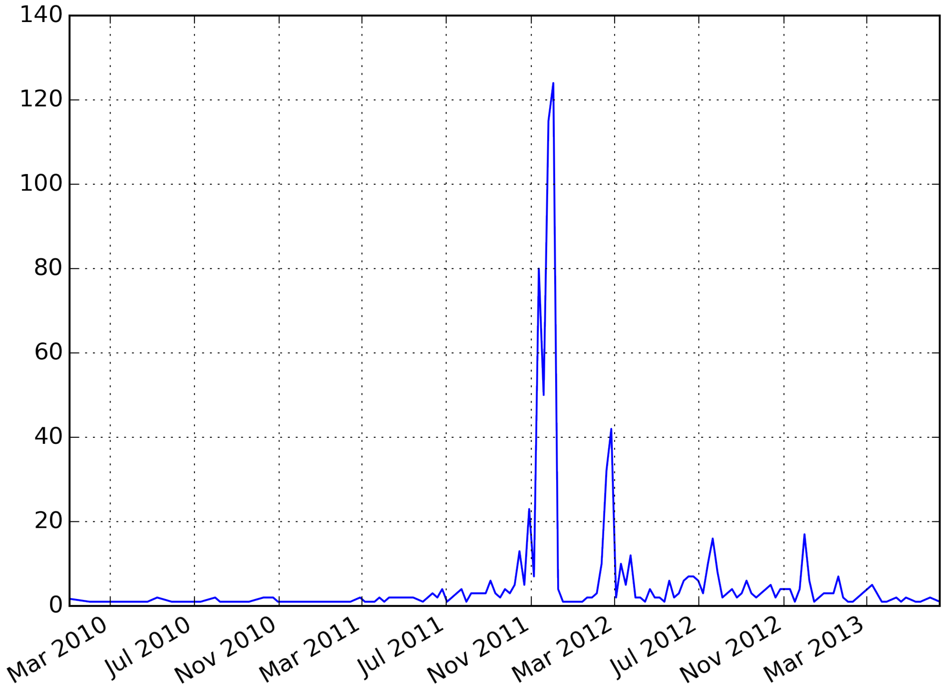


Figure 8.22: Observed adoptions per week in LE2 postcode district

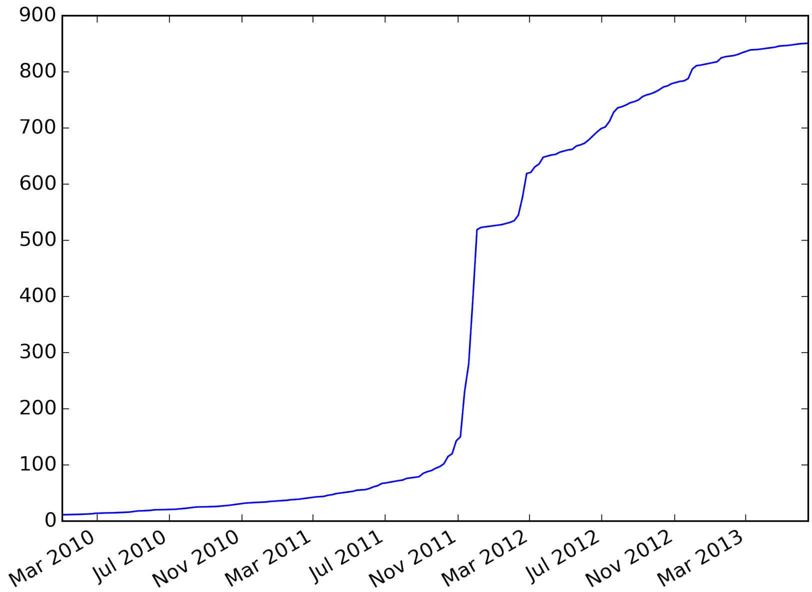


Figure 8.23: Cumulative count of adoptions in LE2 postcode district.

Comparing the shape of figures 8.22 and 8.12a it is clear that the inclusion of the non-economic perception of decision urgency factor produces similar adoption patterns to those observed. The

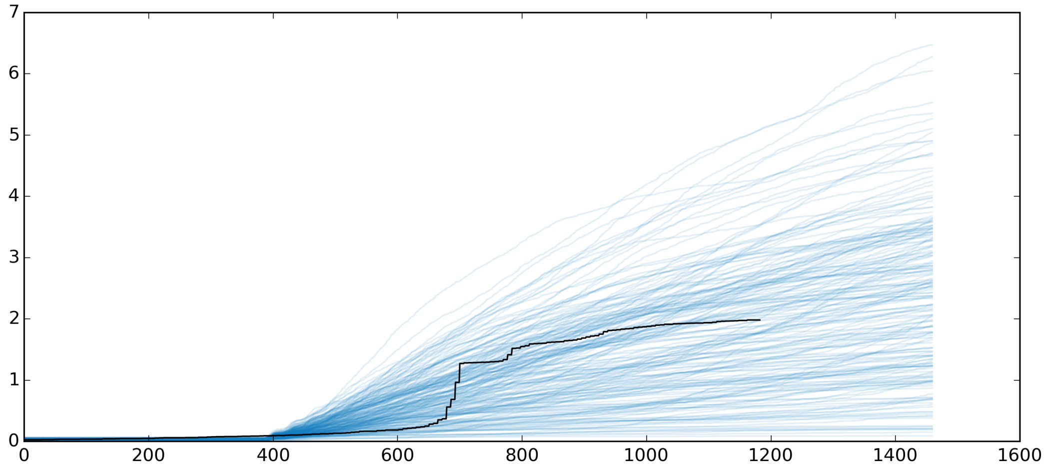


Figure 8.24: Observed data overlayed on model run spaghetti plot

model run described by figure 8.21 does not show such pronounced spikes, but does illustrate the ability of the ABM to model both neighbourhood effects and urgency together.

The absolute adoption observed in real data for LE2 (2.1%) fits within the range of results for several of the parameterisations presented in Table 8.5. An overlay of the cumulative curve (Figure 8.23) with the spaghetti plots for adoption under different social observation parameters, shows that the observed pattern is within the bounds of adoption patterns predicted by the model with r drawn from $r \sim N(10, 7.5)$.

The overlay of data (Figure 8.24) highlights the variation in modelled adoption magnitude under different initial conditions even when the parameters were held constant is large. This reinforces the need to analyse model results in comparison to each other for different parameter combinations and for qualitative effects, rather than as a quantitative predictor of adoption magnitude. The distribution of adoption states at the end of the run is the output that should be interpreted. However, the results from this modelling exercise add to the body of work showing that models incorporating non-economic factors give insight into the potential effects of policy instruments that could not be given by purely economic modelling.

8.4 Summary

An ABM model has been developed and shown to be capable of simulating the effects of policy shocks and vicarious learning via observation, demonstrating the ability to show differing rates of adoption based on the values of SCT constructs c_{OE} and c_{POE}.

For some parameterisations, the simulation outcomes are qualitatively similar to real world observations and can model non smooth evolution of adoption over a time in a way that pure economic or aggregate models cannot. In addition the ABM developed allows for retrospective interrogation of interesting simulation runs and can offer insight into the reasons for certain patterns emerging in a particular parameter combination. In addition, the analysis of distributions of simulation outcome over the full suite of ensembles yields useful information about the effect of assumptions about both average increases in observation amongst the adopting population and heterogeneity in that variable amongst the population. Such insight could be useful when designing policy instruments to encourage smart grid technology adoption in the future.

Chapter 9

Discussion

The data analysed in Chapter 7 clearly show that the FiT has been very successful in promoting the adoption of domestic rooftop PV. They also show that the adoption has been characterised by short periods of intense adoption overlaying a steady adoption rate. The number of PV systems adopted exceeded expectations and predictions of the economic models used in the FiT impact assessment (DECC, 2009). Although there has been some strong political reaction to that success and radical reductions in financial incentives, the number of PV systems adopted has continued to rise in the face of over 50% cuts to the PV FiT. This empirical evidence, in conjunction with the barriers and drivers found in prior work (see section 4.3.2), suggest that factors beyond rational economic decision making are important in the mechanisms governing household adoption. It is evident that the economic models used in the FiT policy design and impact assessment (DECC, 2009), predicated upon rational economic decision making as the predominant factor in the decision to adopt, do not capture important features of the mechanism by which people choose to adopt PV. Whilst the initial greater than expected adoption could be attributed to lower PV capital costs in late 2010 than anticipated at policy design time, the subsequent rapid increase in reaction to policy change cannot. For this reason, the ABM presented in Chapter 8 was developed.

The experiments run with the developed model and reported in Chapter 8 showed the developed model to be capable of modelling social psychological factors in adoption decision making alongside financial considerations. In particular, they demonstrated the ability to model decision urgency as a factor in adoption decision making and showed the effect of both absolute level and heterogeneity of adopter observations on the rate of adoption. Results were presented as output distributions of ensembles run for each parameter combination, highlighting the need to interpret the output from stochastic simulations as distributions. In the case of the ABM developed, the important features are the shape of those distributions and qualitative similarity to observed data, rather than absolute levels of adoption.

The data analysis in combination with the model results demonstrate the considerable influence of behaviour and learning of domestic consumers on the electricity supply system expressed via the patterns of technology adoption. The fact that such effects were not anticipated by policy designers highlights the need for models that have the capability to account for these factors during the design and impact assessment phases for policy instruments designed to encourage low carbon technology adoption. This research has provided one such model.

In the period following data analysis and model development, further data became available detailing FiT registered PV adoption post June 2013. These data show that despite the reduction of tariff to only 30% of its initial level for retrofitted PV panels, adoption continues in a close to linear fashion (Figure 9.1). In the output data from the ABM, a number of runs showed that adoption was still rising gradually at the end of the run, showing that the model developed was able to model the continued adoption observed after the tariff cuts

The high adoption rates under the FiT with respect to domestic PV mirrors experience across Europe where similar schemes have been implemented. Germany and the UK have had high and sustained rates of adoption, with Italy, Spain and France also seeing high rates. Reaction to this has been decisive, with the UK performing the radical rate cuts already described, Germany introducing similar cuts (from more than 50 c/kWh at the start of the scheme to 12.88 in 2015) and Spain cutting even more radically, with a recent proposal to tax self consumption of domestic PV generated electricity, thus taking payback of domestic systems to an estimated 31 years (PV-Tech, 2015; Solar Plaza, 2015). The UK reaction to high rates also prompted a redrafting of the degression mechanism for tariffs and weekly monitoring of installation numbers from January 2012 to March 2014.

To summarise the domestic PV case study, the unexpectedly high installation rates under the policy led to significant reactions by policy makers at national level. The reactions in themselves triggered a very high rate of adoption, probably increasing the final share of the population who adopted PV in contrast to their intentions. Debate has continued regarding the success of the policies, as success is a subjective measure. In general, if one takes the number of installations or installed capacity incentivised as a measure, the scheme can be deemed a success, whereas if one looks to the fraction of electrical energy generation accounted for by distributed PV, domestic PV remains a relatively small proportion. In terms of paths to a smart grid capable of providing significant benefit on a pathway to 2050, these results are important as they highlight

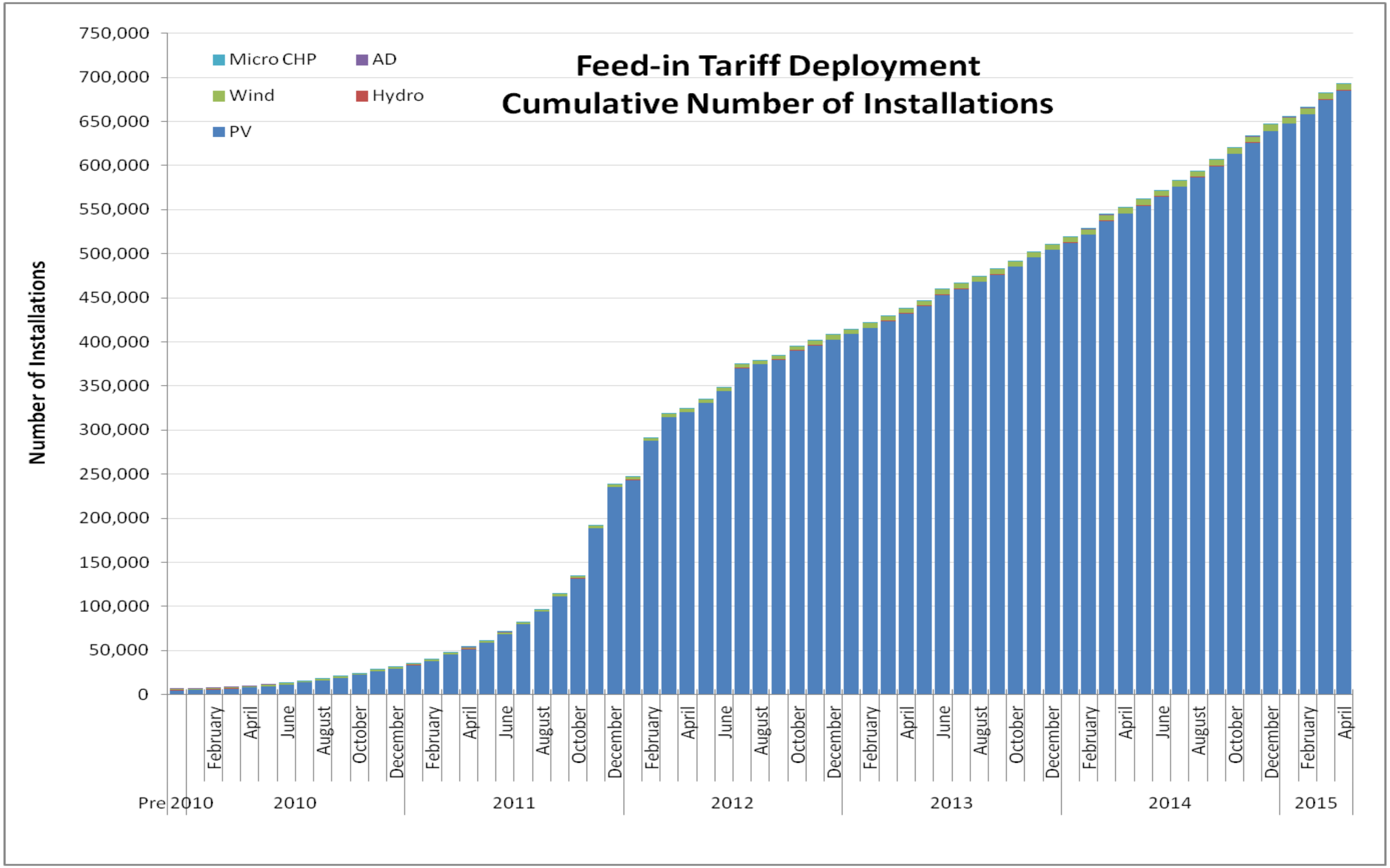


Figure 9.1: Cumulative number of adoptions under the FiT to 2015

the complexity involved in the reaction to policy intervention.

The investigation of domestic PV adoption in response to the FiT is interesting in itself, however it is more important when considered in the wider context of policies intended to ensure that the UK meets its 2050 Carbon commitments by incentivising progress along one of the outlined 2050 pathways. These pathways are inevitably narrow and deterministic, whereas in reality we see a complex mix of influences leading to unexpected or emergent effects.

A very similar policy that has been implemented but has been less successful in the early months of its implementation is the domestic Renewable Heat Incentive (RHI). Despite similar financial rates of return and stated policy aims, the rate of installation of new systems is significantly lower than that seen in the first year of the FiT. This indicates that financial models alone are insufficient to understand the possible effects of an incentivisation policy.

Results from this thesis indicate that while financial incentives have been necessary to trigger PV adoption, non-financial factors have a significant effect on the rate of adoption. In particular, socio-psychological factors such as an adopter's perception of their ability to have the technology installed, the urgency of the decision and the perception of others' behaviour can have significant effects. These effects can manifest as a go / no-go step in the decision making process, rather than the proportional effects based on financial incentives usually modelled in policy impact assessments. Due to the non-linearity of that decision, it is useful to have models to inform decision making that can account for clustering of adopters and stochastic effects of distribution of adopters and their socio-psychological characteristics.

9.1 ABM benefit for policy development

The model developed during this study has incorporated a range of socio-psychological influences on decision making, including but not limited to financial considerations. The use of Social Cognitive Theory (SCT) in this ABM is novel and allows for exploration of the influence of a rich mixture of factors on household decision making with regard to energy technology adoption and the effects of such adoption on the electricity supply and demand system.

The results of the model runs highlighted non-economic factors that have a large influence on the rate of adoption. In particular, the perception of others' behaviour has been shown to be highly influential whether via observation (see the effect of varying neighbourhood definitions in Chapter 8) or via media influence (see the effect of publicised tariff changes in chapter 7 and perception of time to rate change in chapter 8).

Alongside highlighting these important factors, the modelling has also elucidated the wide variation in pathways that may occur under the same policies, with the same overall parameters, simply due to the random variations in starting conditions coupled with interactions during the model runs. This is to be expected in a CAS system; the benefit of the model developed is that it can illustrate potential pathways for consideration by policy makers as well as providing likely bounds on the pathways observed. In particular, the results reported in section 8.3.2.4 show that observation of peers has a marked effect on the mean total adoption observed and is therefore a parameter that policy makers must consider when preparing impact assessments for policy instruments. However, the results also show that there remain a wide spread of potential adoption scenarios for all parameter combinations. Particularly striking is the fact that even in ensembles where the mean adoption rate is high, the high left skew of the output distribution across the ensemble indicates that, due to random variations, there is the potential for adoption to remain low.

This has implications for the use of the SCT based ABM to inform policy developments. It is important to recognise that policy is influencing what is a complex adaptive social system as noted in Section 2.2. Any model of the system is a simplification and for its results to be useful they must be interpreted within this frame. Firstly, as highlighted in section 8.2.4, care must be taken to perform sufficient runs with any parameter combination to ensure that a sufficiently large range of pathways has been covered by the model. Secondly, results should be interpreted as statistical distributions, with certain end states being more or less likely than others, but resisting the temptation to proclaim one particular end state the likely outcome. Thirdly, it must be recognised that the problem of combinatorial explosion of parameter space is a particular problem in this kind of model. Judgement will inevitably be exercised in setting reasonable parameters and allowing random distribution of certain characteristics through the agent population to act as a method for exploring a range of configurations, while accepting that this will never approach the true numbers of combinations that could occur in real implementations. Judgements made in the design of experiments conducted once the model has been implemented must be documented as they form an intrinsic component of model interpretation. Finally, the previous three considerations give rise to an overarching rule for interpretation. The outcomes of the ABM described and used in this work should in general be interpreted as relative to each other, rather than a predictor of absolute outcomes (as noted in section 2.7)

This may seem to limit the efficacy of ABM as a tool for policy development, where the desired outcome is usually a cost of implementation against a benefit. However, it can be argued that the single number cost-benefit approach is flawed and ABM allows a wider exploration of possible outcomes from a policy intervention that can be of great benefit to policy makers in understanding how robust the intervention might be to errors in assumption about human behaviour (for instance under-estimating the perception of installation hassle, or the amount of media attention likely to be drawn to adoption). In a complex system, this insight is invaluable.

9.2 Changes – landscape, regime or niche?

Given the significant and rapid increase in domestic PV installations, it is useful to consider the question of whether the socio-technical regime of electrical supply and use in a domestic setting in the UK is changing. In Subsection 2.4.2, the interpretations of the electricity supply system landscape and regime were given, along with the smart grid as a collection of (currently) niche developments. One such niche is the adoption of PV as investigated in this research. From the perspective of the household, installation, operation and maintenance of a rooftop PV panel is no longer completely unusual and has been absorbed into what constitutes normal features of a house. Roughly 1 in 40 households now have a rooftop PV installation.

However, a radical upheaval of the supply and demand regime has not occurred, rather the regime has evolved. FiTs have been added to the components included in the retail relationship between domestic consumer and supplier of electricity, but the typical relationship remains one where electrical power is purchased by households on a per-unit basis, sometimes with the addition of a generation tariff. Markets, balancing mechanisms and emergency frequency control procedures have not yet changed in response to domestic PV installation under the FiT – domestic generation is still seen simply as a reduction in demand, dealt with by the conventional mechanisms to respond to changes in demand. PV capacity has undoubtedly increased hugely and domestic (FiT attracting) PV accounts for 2.7GW capacity of a total (including all incentive schemes) 7GW PV in the UK (DECC, 2015d).

Verbong and Geels (2010) find that visions of an electricity supply system dominated by distributed generation and focus on local infrastructures would involve a *de-alignment/re-alignment* transition. They also find that such a transition is less likely to occur and depends upon external developments or strong policy intervention. This research supports that view - although the ABM developed suggests that continued adoption is prompted by a combination of adoption and financial incentive, even as that incentive is lessened, the regime of electricity supply system operation has not de-aligned and re-aligned to a new mode of operation based on this widespread adoption.

In the taxonomy of socio-technical transition offered by Geels and Schot (2007) (see section 2.4.1), the FiT has not fostered a transition, rather it represents an incremental innovation characteristic of regime reproduction; a new socio-technical arrangement has emerged as a niche, but the regime has not been deposed or arrangements fundamentally changed. We might refer to the niche as "empowered" cf. (Haxeltine et al., 2008), due to the number of households now participating in the niche arrangements (i.e. generating some electricity via PV), but there has not been wholesale restructuring or deposing of the incumbent regime. For instance, most owners of PV panels retain a conventional pay per kWh supply contract, distribution network infrastructure (cables, transformers) remains the same and balancing mechanisms remain centralised with the system operator retaining responsibility for them. National Grid have stated that:

"Up to a penetration of around 10% of households or 10GW of generation, solar PV can be accommodated on the system without making the operation of the transmission system significantly more difficult."

Source: (National Grid, 2012)

Such incremental innovation may form the precursor to more radical transition, as Geels and Schot note in their taxonomy when describing a sequence of transitions. They characterise such a pathway as being initially imperceptible, but inexorably becoming more dramatic under the *"disruptive change"* of the landscape. They note that

"*'Disruptive change' is a specific kind of landscape development. Because of its slow speed, actors initially perceive only moderate change. As pressure continues to build in a certain direction, landscape change gradually becomes more disruptive.*" (

Source: Geels and Schot (2007))

In terms of the electricity transition and smart grid visions reviewed in 4.1.2 and 4.2 respectively, widespread domestic PV adoption fits most easily into the "Thousand flowers" view of transition, which is itself congruent with the "Groundswell" vision of a smart grid. Both these visions focus on a bottom up transition to smart grid, with local balancing of supply and demand, a focus on local infrastructure and adoption of embedded microgeneration. While this research finds that the latter is happening to a degree, the model runs also show that adoption is potentially subject to wide variation even under similar assumptions about adopter behaviour. The model also provides some support to the view that there is a strong relationship between adoption and observability of the technology. For PV this was a spur to adoption, however it does not bode well for less observable technologies such as smart controllers or heat pumps. In addition to the model, the spatial data analysis also suggests that areas of high adoption are far removed from areas of high consumption - suggesting problems for visions of future scenarios that avoid grid reinforcement costs by balancing supply and demand locally.

If the currently moderate landscape pressures are sustained and build in intensity, we may see a transition along the transformation pathway, with the incumbent regime adapting – adopting new principles and practices without fundamentally changing its configuration. This is particularly relevant as most applications of the MLP to historical transitions look at transitions that happen over the course of several decades. Although the pressure to move to a low-carbon electricity supply system is gaining maturity, the pressure to move to a smart grid is perhaps only 10 years old. The change to a truly smart grid, with bi-directional information and energy flows may necessitate a more radical re-structuring of markets, supply chains and infrastructure. Such radical transitions seem unlikely at this point, particularly as the political economy seems to be transferring focus away from incentivising a low carbon, smart grid enabled, electricity supply system.

9.2.1 Landscape changes - policy

During the course of this research, the complexity of policy development in energy systems has been evident throughout. In addition to the changes to FiT highlighted earlier in this thesis (Chapters 3,7), a further extraordinary review of FiT tariffs has been initiated in 2015, with a proposal to reduce tariffs for domestic PV installations to only 1.63 pence per kWh (from 12p/kWh at the time of writing and 43p/kWh initially). The ABM in this thesis could be used to examine the potential effects of this reduction in terms of the likelihood of it reducing the number of future adoptions and therefore whether it will meet the stated primary objective to "control costs effectively in a way that is consistent with the UK's undertaking in its State Aid approval" (DECC, 2015b, para. 3.1).

This represents an interesting development from the MLP perspective. The success of the FiT has begun to empower a niche actor – the PV owning domestic prosumer. The rise of such a prosumer, especially if allied with adoption of technology to increase self consumption (e.g. Immersun and competitors), could be seen as a challenge to the incumbent supplier-consumer regime as prosumers became increasingly independent of supply from the centralised grid. The reaction of the state can be seen as one that is reacting against this empowerment to maintain the incumbent regime. There is now an explicit objective to curb the rate of adoption of domestic PV. The necessity to justify state subsidy is cited as a reason for this, but funding for FiT is provided via levy on all electricity customers so, while this could be viewed as a state supervised transfer of money from all consumers to those with installed micro-generation, this is perhaps not what most people would understand to be state subsidy.

Alongside the FiT changes, other changes have occurred in the electricity generation landscape. For instance, The largest generator in the UK, DRAX announced that they would no longer introduce Carbon Capture and Storage (CCS) at their facility (BBC, 2015). While this does not directly influence the adoption of distributed generation or the smart grid, the withdrawal of a large regime actor from a large scale carbon reduction project will undoubtedly perturb the complex system – sending a signal that carbon reduction is not financially viable nor a commercial priority while at the same time increasing the necessity for a smart grid to utilise local small scale for carbon reduction in tandem with reasonable prices for consumers.

Ofgem note the increase of embedded generation as a reduction in peak demand on the national transmission level (note that this includes domestic microgeneration, but also significant amounts of commercial embedded generation):

"*In our Capacity Assessment 2014, we identified that the risks to security of supply were increasing up to 2015/16 as a result of plant closures. Since we published our 2014 report, more plant have exited or announced their intention to exit the market permanently or temporarily. This has been partly offset by a reduction in peak demand at the national transmission network level since last year: National Grid believes this is mainly due to increased contribution from embedded generation (seen as negative demand by National Grid at the transmission level)* ."

Source: (Ofgem, 2015)

Rather late in the FiT life cycle, the unintended effects of tariff degression has been recognised by government. In the impact assessment for the latest consultation on FiT review, it is noted that:

"*Given that pre-accreditation spikes have remained high over time, particularly for hydro, it suggests that the tariff reductions are insufficient to manage deployment and spending, as was intended within the 2012 review.*"

Source: DECC (2015b, para. 1.7)

Finally, following the completion of the EMR, Contracts for Difference (CfD) are intended to be the main instrument to encourage installation of further renewable energy installation. At the present time, it is not clear how smart grid technology will be incentivised within the CfD framework, but it seems clear that the pressure in the political landscape is to move away from the FiT at this point. In summary, the policy changes enacted during the course of this research, along with the proposed changes at the time of writing, indicate that a reconfiguration of the electricity supply system to a smart grid based on local embedded generation remains at a distance, if it is to happen at all.

9.3 Complexity

The pathways developed by both policy makers and researchers to illustrate possible evolutions of the current electricity supply system to a smart grid and the energy system to meet 2050 Carbon emissions targets are presented as archetypes and can appear simplistic. For instance, Shove and Walker (2014) criticise the 2050 pathways in strong terms, arguing that they *"...fail to engage in any meaningful way with the basic dynamics of demand. Instead, the strategy is to take present practices entirely for granted..."*. The critique is founded upon the fact that the pathways focus on technological and resource changes over time and fail to consider the social aspects (in the case of this particular critique, social practices) that shape the use of the energy system. The authors postulate that it is *"difficult, and perhaps impossible, to predict how social practices will change"*. The danger from this line of argument is that it could lead to a position where no policy intervention toward desired goals is undertaken, because it is impossible to understand the outcomes of a policy within such a complex system.

The systems that the pathways describe are complex and the number of interactions that may occur both within the system and between the system and its context is large. In this situation, it is useful to prepare pathways that show broad spectra of possible outcomes, rather than outline a set of paths that seem discrete and pre-determined. This is a lesson that, for example, climate modellers have had to learn, as their models have been taken and used deterministically to shape policy, only to suffer form continual attack when their precise outcomes do not occur. The task of presenting stochastic models and ranges of possible outcomes with associated likelihoods is not an easy one. However, it is necessary if we are to produce policy to reduce carbon emissions via a smart grid that are robust to changes in global political economy as well as people's preferences within the UK.

This research has contributed a model (and contributed toward a methodology) that supports a probabilistic development and understanding of pathways toward a less carbon intensive energy system. The advantage of the model presented is that it allows for explicit consideration of the socio-psychological characteristics of actors within the energy system when designing policy intended to change their behaviour. It cannot be argued to eliminate all assumptions about which practices will remain in a low carbon future. Nor can it be argued to capture the full diversity of how actors may interact or behave in response to a policy. However, it can give insight into possible pathways that may be followed by both individuals and the system in aggregate under certain policy incentives. This is useful to policy makers as it can aid understanding of how the same policy may fail or over achieve in its objectives, depending upon random distributions of characteristics within a simulated population. This in turn can be used to investigate a policy's sensitivity to various factors of interest to the policy maker at design time.

9.4 Applicability of the model

The ABM developed has been shown to be a suitable method to explore potential reactions to policy to incentivise adoptions toward a lower carbon, smart energy system. The method avoids some of the need for expensive and risky trials, whilst providing the opportunity to incorporate data from such trials or from country-wide observations. Using the quantitative modelling and data analysis results in conjunction with qualitative analysis within a transitions framework gave insight into the implications of the modelling in terms of qualitative system change. This indicates that such an integrative method is more suitable to assessing potential effects of incentivisation policy than other methods such as a conventional economic approach, or a pure sociological or psychological method. This use of quantitative methods (computational modelling and adoption data analysis) in conjunction with qualitative analysis of policy and modelling results has proved to be useful in this context. Recently, Turnheim et al. (2015) have advocated the use of a similar workflow to study (in their words *"Bridging analytical approaches"*) to study sustainability transitions, combining quantitative systems modelling and socio-technical transition studies as in this research with initiative-based learning - a grouping that they acknowledge to be somewhat loose, but by which they mean study via the observation of local initiatives to understand the motivations of relevant actor in enacting system change.

The benefit of hybrid methodology is clear: policy making can benefit from models to generalise the findings from small scale experiments to system wide effects, or from large scale aggregate data to potential local effects, however it is prohibitively expensive to test initiatives to change very large infrastructure systems on the whole system. A hybrid method, which can take data and insight at multiple scales, model the system informed by that data and then provide analysis of potential initiatives to policy makers with an appropriate mix of quantitative and qualitative interpretation, is invaluable. ABM used as presented in this research offers that potential, allowing prior findings from psychology and studies of sustainable technology adoption to be incorporated into a model that is informed by national scale adoption, geographic and weather data. Socio-technical transition theory (in this case the MLP in particular) then offers a useful framework within which to judge whether a given intervention is likely to make changes to the system as a whole.

The research and methods presented in this thesis have proved effective in gaining insight into the reasons for the observed behaviour under the FiT, as well as exploring whether some of the unexpected developments could have been foreseen with appropriate modelling. The model results demonstrate that observed behaviour was within the patterns that could have been shown to be plausible by an appropriate model such as the one developed within this work. Methodologically, the work adds support to the argument for the use of social psychological models to inform ABM decision making.

9.4.1 Limitations and generality

The work presented in this thesis inevitably has some limitations. The most telling limitation has been practical, time has not allowed for a greater range of parameter combinations to be explored. This is a limitation that will often be encountered when using an ABM with a focus on description rather than simplicity. The range of parameter combinations becomes extremely large, such that a full exploration of the entire parameter space would always be impractical and will often be limited by time or computational resources. To ameliorate the effect of this limitation, judgement has to be exercised as to interesting parameters to vary and interesting ranges within which to vary them. That has been done in this research and has led to the learning described earlier in this chapter. To some degree, any model can be said to exhibit this problem in that it can only describe the phenomena for which it has been designed and parameterised. The infamous quote that *"all models are wrong, but some are useful"*[1] (Box and Draper, 1987, p.424) applies just as well to a parsimonious rational economic model as it does to the ABM developed here, although the limitations of the state space here are perhaps more explicitly displayed.

This in turn relates to the use cases for such ABMs. This type of ABM can incorporate social phenomena in a way that is not possible for the economic models so often used in policy-making and impact assessment. Howevever, as set out in section 2.7, it does indicate that this class of model is most useful for informing qualitative decision making and understanding about potentially significant factors within the adoption of technology. It is clear that the economic models used in the FiT impact assessment failed to capture the potential for somewhat faster than expected adoption in conditions where PV prices were falling, the tariff was generous. The model produced here could have shown that such a scenario was possible with certain configurations of early adopters and observers and that the adoption prior to early 2011 seen was within the bounds of what could have been reasonably expected. It is even more clear that the policy-making response to the perceived over adoption failed to anticipate the magnitude of adoption that would be stimulated by the early retrenchment in tariff, pushing the adoption curve onto a far higher trajectory. Qualitatively, the ABM produced here could have simulated that effect and given a range of outcomes depending on the modellers view of how strong that effect would be. This would still leave the policy-maker to exercise judgement, but with some insight from the

[1] for an interesting counterpoint to this oft-quoted phrase, see "all models are right, most are useless" : http://andrewgelman.com/wp-content/uploads/2012/03/tarpey.pdf

simulation run.

A further limitation is spatial extent. Although this model pushes toward spatial realism and incorporates a fairly large number of agents, adding another order of magnitude (or two) to the model in order to simulate sizable portions of the UK population at large would be infeasible if the temporal resolution was to remain the same. It would be possible to downgrade the temporal resolution (currently it uses the CASCADE standard half-hourly time tick in order to allow monitoring of demand profiles alongside other parameters), but even this would only be useful to a certain point and would lose some richness within the result set.

The ABM developed requires a large amount of data collection and analysis to inform its parameterisation, as well as to inform analysis of the outcomes it produces. This raises questions about its generality. In terms of the basic adoption model developed, an SCT decision model could be applied to other technologies. An amount of research would have to be done to map relevant data to the constructs identified and to gather information about those parameters, as has been demonstrated for the case of PV in this work. In addition, given the spatial extent constraints mentioned, additional techniques would be needed to understand the differences in magnitude between spatial units - even if the spatial unit adopted has been shown to be of the right size and representative of the country at large as was the case here (section 7.7).

9.5 Summary

The ABM developed has shown the capability to model the effect of some elements of behaviour and learning of domestic consumers on adoption of PV systems, in a way that cannot be achieved by standard aggregate adoption models, or the economic models conventionally used in impact assessment for policy instruments (such as those described in Chapter 3). When an ensemble of ABM simulations is run, the results are an output distribution for a given parameter combination. This gives an indication of the distribution of potential outcomes, created from the bottom up. The use of distributions such as these rather than the single numbers (sometimes with normalised error margins) to inform policy making is useful. In addition, the ABM runs yield data which allow for examination of particular runs, which may be outliers, to gain insight into particular pathways where policy instruments encourage far lesser (or greater) adoption than economic models would predict. The modelling method has limitations, in terms of the parameter space and spatial extent which can be explored, but nonetheless provides extra insight into the potential effects of a policy intervention. The ABM developed here has the potential to allow for more technology types or agent parameters to be added, without fundamental changes to its algorithms.

In combination with data analysis, the approach gives a rich picture of the mechanisms of adoption and the potential for the adoption to become normalised in society. In the case of PV, the model shows that the social influences of observation and reaction to policy changes have contributed to the observed widespread adoption, alongside economic incentives. Many runs within the model ensembles show adoption continuing to rise after tariff cuts as observation continues, which is congruent with real world observations. This can inform studies of transition in the electricity supply system, particularly while such a transition may be ongoing, as is the case with the UK's potential transition to a smart grid.

The model gains more power when combined with policy and data analysis. Data analysis shows that PV system ownership has become somewhat commonplace, with 2.5% of UK households now having registered PV on their rooftops. However, the spatial analysis tool developed and used in this thesis shows the distribution of those systems across the country to be somewhat static and potentially problematic for visions of a smart grid. In particular, it demonstrates clearly that the centres of high consumption (the large cities) have a very low proportion of microgeneration adoption, which makes it hard for visions of locally balanced smart grids limiting loads on infrastructure to become reality. Analysis of the statements of grid operators alongside policy indicate that microgeneration adoption has been accommodated within the normal regime of operation. In MLP terms, policy and weight of numbers owning PV may be applying gradual landscape pressure and the niche gaining power, but it is hard to say with any certainty that a transition is under way. Observations about the geographical positioning of microgeneration and policy statements are contra-indicators that a transition toward a smart grid with localised generation balancing demand to limit load on the grid is about to occur. Policy developments in 2015 may indicate that the business as usual hierarchical regime is reacting as policy incentives for localised microgeneration are removed and large scale projects such as nuclear power station building are given the green light.

Finally - the spread of outcomes produced by the ABM even within the same parameter combinations indicate the care that must be taken to acknowledge the complexity and adaptive nature of the system under consideration. The model results should be interpreted as distributions and the relative results for parameter combinations analysed, rather than absolute levels.

Chapter 10

Conclusions and further work

The aim of this study was to investigate the question *"what effect does the behaviour and learning of domestic consumers with respect to technology adoption have on potential transition to a smart grid?"*. A better understanding of such effects would be of great utility to policy-makers designing policy instruments to promote transition to a smart grid. This PhD study has contributed results that should improve understanding in particular of how the policy landscape, local conditions and individual actions reciprocally influence each other when considering technology adoption as part of such a transition.

The literature reviewed indicated that the adoption of technology had a significant and long lasting effect on consumption patterns as compared to behaviour change alone, even where behaviour change was motivated by variable (or smart) tariffs (section 4.4). In consideration of this, consumer behaviour and learning applied to technology adoption as opposed to direct behaviour change was considered. To understand the mechanisms and factors affecting technology adoption in a smart grid context, PV was used as a case study technology. PV is considered to be a representative smart grid technology as smart grid visions all incorporate distributed renewable generation. It has the added advantage for study of having substantial adoption and data available. It is envisaged that insight from this case study can be generalised and used to understand the potential patterns of adoption for other technologies affecting proposed smart grid scenarios.

The policy review showed a complex web of policy that affects the transition to a smart grid in the UK, ranging in scale from EU-wide targets to obligations on local areas and with objectives based on any combinations of the three components of the energy trilemma (section 1.2) – security of supply, affordability or environmental sustainability. These policies form part of the socio-technical landscape for the electricity supply system and a potential transition to a smart grid. During this research, the main policy affecting the domestic PV adoption used as a case study (the FiT) has changed quite radically. In addition, the energy policy landscape and political economy more generally has changed. The effect and interpretation of these changes are discussed below (section 10.1).

The data analysis undertaken showed that the uptake of PV under the FiT followed a path that was at the higher end of expectations. The data analysis demonstrated that interventions to limit that growth had two effects

1. **In the short term** – the announcements of changes to an attractive incentive scheme and the associated media interest caused rapid increases in adoption. This, in turn, increased the strength of social influence to further increase adoption.
2. **In the longer term**, the rate of adoption settled into a broadly linear pattern (Figure 9.1), but on a higher trajectory of adoption.

The pattern of adoption, particularly the spatial and temporal clustering, indicate that factors other than rational economic decision making were important and should be included in a model of adoption that sought to explain the patterns observed. Consideration of the effect of social learning via observation as performed using the model developed in this study indicate that the present rate of adoption may have been reached with less severe interventions – for example by following the pre-determined degression.

In addition, the data analysis showed that adoption could not be adequately modelled as a simple function of demographic variables which might, *prima facie*, be expected to explain the adoption, for instance the local density of population, indices of multiple deprivation or fraction of owner occupiers. While these variables did correlate to some degree with differences observed between localities (section 7.6), they could not explain the temporal evolution of adoption patterns either within or between localities.

The data analysis tool developed to visualise and analyse the evolution of spatial distributions over time has proven to be powerful (e.g. section 7.2.3). In the case of PV it clearly demonstrated that the spatial distribution of PV installations remained similar over time, although the absolute magnitude was subject to spikes at particular times. This highlights both the importance of physical landscape factors (the South West has persisted in being a high installation area and is also the area of the UK with the highest insolation) as well as the importance of "seeding" in technology adoption (those places with relatively high adoption at the commencement of FiT remained so - even where locations may not have appeared to be prime locations for PV due to insolation. The apparent stability of the spatial distribution of adoption has important implications for visions of smart grid futures. The areas of high consumption, such as large conurbations, also show low adoption of microgeneration. This implies that visions of highly distributed generation with localised infrastructure balancing supply and demand to minimise the load on, and expansion cost of, the grid at large will be hard to achieve even with the widespread PV adoption experienced under the FiT.

A final conclusion of the spatial data analysis was that adoption patterns in 95% of postcode district followed the same pattern as the national adoption pattern (section 7.7). This analysis gave a quantitative basis for deciding that postcode districts were the appropriate spatial scale for representative modelling.

This work has introduced a new model of PV diffusion, an ABM based on the CASCADE[1] framework. This model has allowed exploration of a complex mix of influences on the rate of adoption of PV at the Postcode District level. The process of model development required identification of influential human behaviours in terms of their contribution to a smart grid and development of a method to encode them in an ABM. The model made use of Social Cognitive Theory (SCT) as the basis for a decision making algorithm for households. This is a new basis for decision making in an ABM and has been shown to be suitable for modelling PV adoption. The SCT model is useful for modelling human agents in a situation where decisions must be repeatedly evaluated in the context of personal characteristics, social influences (e.g. observation of others' adoption) and changing policy (socio-structural factors). Methodologically, the ABM supports the use of well-established social psychological theories as the basis for modelled decision making.

Use of the model has given new insight into the explanation of observed PV adoption, in particular the effects of the vicarious observation on adoption rates in combination with endogenous characteristics. It was found that both the breadth of vicarious observation undertaken (radius of observation in this model) and the heterogeneity in this characteristic were significant in the modelled uptake.

Focusing on the LE2 postcode district as the simulation area, the observed adoption under FiT was within the bounds of simulated adoption using the ABM developed in this PhD. This is

[1] Development of the model employed within this research formed a significant contribution to the CASCADE framework for modelling the UK electricity supply system.

in contrast to the purely economic scenarios used in the FiT impact assessment, where observed adoption exceeded the highest expected rates. Cutting the FiT actually increased the adoption rate in the short term, an effect the model presented here could capture (section 8.3.1). The observed effect of that was to push the adoption curve onto a higher trajectory - something that the developed model could also simulate as it accounts for the impact of higher observed adoptions on future adoption behaviour.

The modelling work showed that, although the observed domestic PV adoption under FiT was at the higher end of plausible adoption outcomes, the model developed over the course of this research could have shown that to be a possibility, illustrating the potential utility of the developed model for policy-makers.

The modelling method combined a decision model based on psychological theory with the use of real-world geography in a spatially explicit ABM of product diffusion. This builds on prior work using similar techniques (Zhang, 2011; Zhang and Nuttall, 2011; Robinson et al., 2013, e.g.), introducing the use of Social Cognitive Theory as the psychological basis. The model been found to be effective when modelling adoption which relies on vicarious observation as it inherently accounts for lessened observation in sparsely populated areas.

10.1 A transition in the complex electricity supply system?

The data analysis conducted in this study shows that there has been a significant increase in the ownership of domestic PV between the start of the FiT policy and mid 2015. It further shows that the pattern of adoption across time cannot be fully accounted for by gross demographic variables. Social Cognitive Theory (SCT) has proven to be a useful model to bring social, economic and individual factors together into a decision making algorithm within an ABM. The modelling work demonstrates that perception of decision urgency (outcome expectation) based on a change in socio-structural factors (the FiT review) has a significant impact on the temporal pattern of adoption and that the level and heterogeneity of vicarious observation in the population (the perception of others' behaviour) has an effect on both the spatial distribution and absolute level of adoption. This indicates that models taking explicit account of such social factors have utility in modelling the range of likely outcomes for given policy interventions.

The data analysis show the substantial effect of behaviour and learning in domestic consumers with respect to technology adoption, while the model developed provides some insight into the mechanisms involved in creating that effect, as well as providing a rich environment to test those insights and assumptions regarding adopter behaviour. The secondary clause of the research question dealt with the context of the transition to a smart grid. While still a niche, it is plain that the PV owning niche has grown in number – nearly 2.5% of the households in the UK are PV owners. However, this does not mean that the regime of electricity supply has been deposed, still less that the system has transitioned, or has even begun a transition, to a smart grid. National Grid, the system operator, still views domestic PV generation as simply a lack of demand within the incumbent operating regime (National Grid, 2012) and the government is moving to lessen the incentive for more households to join the PV owning niche (DECC, 2015c). The modelling work undertaken here shows that the impact of PV generation as a proportion of domestic demand remains niche.

As discussed in section 9.2, the rise in domestic PV generation does not obviously herald a transition to a smart grid at the time of writing. Currently the data analysis and modelling show that while domestic PV adoption has increased dramatically, generation is modest, whilst the policy analysis shows the regime to be in a dynamic equilibrium, reproducing the same modes of operation albeit accommodating a greater amount of domestic microgeneration. However, referring back to the typology of transitions proposed under the MLP (sections 2.4.1 & 9.2) it is possible that we observe the early stages of a sequence of transitions which may lead to such an outcome. Such a sequence is characteristically hard to detect initially. There is some indication that the growth in domestic PV adoption has led to an increased appetite for (smart) devices to displace demand in the household in order to increase domestic self consumption. Such developments could provide fertile ground for further work using the developed model (section 10.4) and may be the seeds of a transition towards a "Thousand flowers" pathway towards a smart grid as described in section 4.1.2.

10.2 Policy impacts

As well as developing and implementing a modelling approach that could inform policy-makers by projecting the effect of policy instruments explicitly considering non-financial factors, this research makes a contribution to the academic debate on energy policy. The data analysed and modelling undertaken showed that the FiT certainly incentivised the adoption of one technology required for a transition to a smart grid, but that the effects are not easily predictable, nor are they intuitive. An example of this is the observed "spikes" in domestic PV adoption (section 7.2.2). The research indicates that policy makers should be mindful of the urgency perceived by potential adopters and observation when designing policy to incentivise adoption as part of a smart grid transition. The model demonstration that heterogeneity in observation increases adoption without an increase in average observation is useful; it could mean that ensuring that adoption is observable, even to a few potential adopters spread throughout the population, is a worthwhile goal for those wishing to increase adoption overall.

The research has found that the factors influencing adoption of technology over the population of households are manifold and interact in complex, sometimes subtle, ways. Many studies of technology adoption have focused on the rational economic behaviour of adopters, but the analysis and modelling undertaken in this research has demonstrated the significant influence of non-economic factors. In section 8.3.2.4 we see that both the amount and heterogeneity of observation can have a very large effect, changing average adoption between 0.03% and 40% at the extremes tested. This implies that assumptions by policy makers on the amount of observation associated with adoption is very important and should be explicitly considered within the design of policy intended to incentivise adoption. The model developed has the capability to model these factors and has shown their influence when running scenarios where only the non-financial parameters were varied. The ABM also demonstrates that the variety of possible outcomes from a single parameterisation - supporting the case for using distributions as model outputs rather than single numbers as is typically the case for economic scenario models.

The ABM model developed demonstrates that ABM can provide a testbed to more easily encode the complex interacting factors that determine reaction to a policy instrument. Such a testbed then facilitates scenario generation with multiple parameter combinations, allowing multiple policy designs to be quickly simulated as well as exploring assumptions around household or individual characteristics. This work explored in detail the implicit assumption of how widely potential adopters observed other adopters when making an adoption decision and showed it to be a crucial factor in decision making which, while acknowledged in policy design, was not evaluated. This factor is important in PV adoption, however other assumptions can be tested in this way - as could different policy designs such as capital subsidy for installation or different tariff levels.

This capability would be of use to policy-makers both in the policy design stage and when attempting to predict the effect of interventions changing policy (such as the extraordinary reviews of the FiT). The ABM methodology allows assimilation of knowledge from various sources. As shown in this study, empirical data from individual households can be used to determine appropriate decision models, while national scale data can be used to parameterise the context in which agents operate. As mentioned in the chapter 1, ABM is perhaps more useful in identifying scenarios that are very unlikely to emerge and offering a range that might than predicting exactly which one will. Use of ABM will require policy-makers to embrace this form of modelling, where outputs can be likelihood distributions, rather than a single hard outcome per policy. There is some evidence in more recent development of similar policy (for instance the renewable heat incentive in the UK) that the necessity for this is at least acknowledged.

Finally, the model developed offers policy-makers a methodology to scale small empirical studies to nationwide systems. Most studies of the psychological factors influencing adoption behaviour specifically in the domestic electricity sector are small scale, a psychology study with N=300 would be considered large scale, however there are 23 million households in the UK and, for domestic agents to have large impact and become significant in a transition to a smart grid, large sections of this population must adopt technology. The ABM model and methodology developed in this work provides a tool which can take the results from the small scale studies and encode the parameters found to be significant from those. The model can then be used to perform simulations on much larger synthetic populations endowed with a realistic decision model, but in which the parameters can be varied to test the effect of potential differences, such as regional characteristics or assumptions about relative influence of, for instance, economic and social factors. This is an advance on most previous models, which have been limited to a small number of economic scenarios. The ability to include social factors in policy models is inherent to the model described in this work and gives the ability to test policy intervention with a range of assumptions about social factors that would be difficult, expensive or unethical to test in the real world.

10.3 Recommendations

The research suggests a number of concrete recommendations for policy makers:

1. Data analysis (Chapter 7), prior literature (Balcombe et al., 2015; Jager, 2006; Consumer Focus, 2012, e.g) and model results (Chapter 8) show that it is essential that influences on domestic adopters beyond their rational economic response are considered at policy design time. The research suggests that non-financial factors are important in the decision to adopt and should be researched at policy design time and incorporated into impact assessment.

2. Policy makers could commission Agent-based models of technology adoption when designing policies to incentivise those. The model developed for this research, using Social Cognitive Theory as the basis for decision making has been shown to have utility in modelling the spread of adoption scenarios possible under a given policy and could be used by policy makers.

3. When assessing the impact of policies to incentivise technology adoption in future smart electricity networks, it is important that policy makers consider the distribution of possible outcomes in response to a given set of policy parameters, rather than a single number, which might represent an average or expected outcome.

4. When considering the change of incentive over time, the range of adoption rates that could be reasonably predicted at design time should be considered and mechanisms implemented that can alter the incentive without delivering undue "shocks" to the system.

5. In considering the impact of policies in terms of its contribution towards a future smart grid, policy makers should consider the spatial and temporal distribution of adoption in addition to the overall numbers adopted. If a policy objective is adoption at particular rates in particular regions, consideration should be given to locally differentiated incentives.

10.4 Further work

The tools and techniques developed over the course of this research are suitable for further use. Below are a number of questions which would be appropriate for further work, but which time and resources meant were excluded from the scope of the research.

1. This work contributes research towards an understanding of the adoption of low carbon technologies in the context of a transition to a smart grid. An interesting further topic for research is the interplay between adoption of different technologies, only touched upon in this study. As many technologies become mainstream (for instance, heat pumps, electric vehicles, domestic storage) these effects may become more significant and would merit further investigation.

2. The modelling effort in this research has used the assumption that installation firm capacity is infinite and can grow at infinite rate. It also takes no account of the availability (or change in availability) of installation services on the rate of technology adoption. These factors would form the basis of an interesting study and could further inform policy designed to accelerate adoption of any combination of technologies.

3. The tool to study spatial distributions over time has been used to examine PV adoption, however it has the capability to visualise any variable plotted across space and time. The examination of weekly, seasonal and annual variations in spatial distributions of, for instance, consumption or embedded generation would provide an interesting area of further study.

4. A large scale empirical study (or studies) could be used to inform models of agent decision making with fewer assumptions than have been necessary in the course of this research. This would require substantial funding, or collaboration with a large organisation with such funding.

5. Extension beyond domestic agents. An interesting and fertile area for further study is the introduction of larger scale (community, commercial and industrial) agents with the ability to adopt in a similar fashion to the domestic agents modelled here.

6. Heterogeneous decision models. This research has used heterogeneous agents, in that they have a wide spread of parameters in various areas. However, agents representing real world entities of a similar type (e.g. households) have not been given entirely different decision models. It would be useful to extend the study to mix, for instance, a number of purely

rational decision makers with entirely network influenced decision makers, alongside the SCT decision makers modelled in this work.

7. Adoption of practices and contracts - as well as adopting technology, a transition to smart grid requires that householders participate in new styles of contract and use the electricity system differently. There is potential for models similar to the one used in this research to give insight into the potential for adoption of such contracts and use behaviours.

10.5 Summary

The research presented in this thesis has shown the benefits of a new ABM utilising a decision making algorithm based on Social Cognitive Theory to model the adoption of PV in the UK. Applying insight from the quantitative results to the wider context of policies designed to incentivise technology adoption in a future smart grid has yielded practical recommendations for policy makers to use the results of such models during policy design. These contributions constitute a step towards greater understanding of pathways to a smart grid; further work to build on this research has been suggested, some of which the author looks forward to tackling!

Bibliography

S. Acha, K. H. van Dam, J. Keirstead, and N. Shah. Integrated Modelling of Agent-Based Electric Vehicles into Optimal Power Flow Studies. In *21st International Conference on Electricity Distribution, Frankfurt*, pages 6–9, 2011.

AECOM. Energy Demand Research Project Final Analysis. Final project report 60163857, Ofgem, London, June 2011.

I. Ajzen. The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211, 1991.

ARUP. UK Energy Legislation timeline (Edition 3), February 2011. URL http://web.archive.org/web/20110305162233/http://www.arup.com/Publications/UK_energy_Legislation_Timeline.aspx.

ARUP. UK Energy Legislation timeline (Edition 6), September 2012. URL http://web.archive.org/web/20121229173833/http://www.arup.com/Publications/UK_Energy_Legislation_Timeline.aspx.

ARUP. UK Energy Legislation timeline (Edition 9), April 2016. URL http://publications.arup.com/publications/u/uk_energy_legislation_timeline.

National audit office NAO. Infrastructure investment: the impact on consumer bills, November 2013. URL http://www.nao.org.uk/press-releases/infrastructure-investment-impact-consumer-bills/.

Graham Ault, Damien Frame, Nick Hughes, and Neil Strachan. Electricity Network Scenarios for Great Britain in 2050. Technical appendices 157a/08, Ofgem, London, November 2008. URL https://www.ofgem.gov.uk/ofgem-publications/55666/157018blensappendices.pdf.

Lisa Bachelor. Feed-in tariff starts to generate cash. *The Guardian*, April 2010.

ISSN 0261-3077. URL http://www.theguardian.com/money/2010/apr/01/feed-in-tariff-green-energy.

Paul Balcombe, Dan Rigby, and Adisa Azapagic. Energy self-sufficiency, grid demand variability and consumer costs: Integrating solar PV, Stirling engine CHP and battery storage. *Applied Energy*, 155:393–408, October 2015. ISSN 0306-2619. doi: 10.1016/j.apenergy.2015.06.017. URL http://www.sciencedirect.com/science/article/pii/S0306261915007758.

Catherine SE Bale, Nicholas J. McCullen, Timothy J. Foxon, Alastair M. Rucklidge, and William F. Gale. Modeling diffusion of energy innovations on a heterogeneous social network and approaches to integration of real-world data. *Complexity*, 19(6):83–94, 2014.

Nazmiye Balta-Ozkan, Tom Watson, Peter Connor, Colin Axon, Lorraine Whitmarsh, Rosemary Davidson, Alexa Spence, Phil Baker, and Dimitrios Xenias. Scenarios for the Development of Smart Grids in the UK: Synthesis Report. Research Report UKERC/RR/ES/2014/002, UKERC, London, January 2014. URL http://www.smartgridscenarios.org.uk/wp-content/uploads/2014/02/Scenarios-for-the-Development-of-Smart-Grids-in-the-UK-Synthesis-Report.pdf.

Albert Banal-Estañol and Augusto Rupérez Micola. Behavioural simulations in spot electricity markets. *European Journal of Operational Research*, 214(1):147–159, October 2011. ISSN 0377-2217. doi: 10.1016/j.ejor.2011.03.041. URL http://www.sciencedirect.com/science/article/pii/S0377221711002785.

A. Bandura. *Social foundations of thought and action*. Prentice-Hall, Inc., Eaglewood Cliffs, New Jersey, Stanford University, 1986.

A. Bandura. Social cognitive theory: An agentic perspective. *Annual review of psychology*, 52(1): 1–26, 2001.

Albert Bandura. Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, 84(2):191, 1977.

Albert Bandura. Human agency in social cognitive theory. *American psychologist*, 44(9):1175, 1989.

Stewart Barr, Andrew W. Gilg, and Nicholas Ford. The household energy gap: examining the divide between habitual-and purchase-related conservation behaviours. *Energy Policy*, 33(11):1425–1444, 2005. URL http://www.sciencedirect.com/science/article/pii/S0301421503003859.

Frank M. Bass. A new product growth model for product diffusion. *Management Science*, 15(5): 215–227, 1969.

Frank M. Bass, Trichy V. Krishnan, and Dipak C. Jain. Why the Bass model fits without decision variables. *Marketing science*, 13(3):203–223, 1994.

D. Batten and G. Grozev. NEMSIM: Finding Ways to Reduce Greenhouse Gas Emissions Using Multi-Agent Electricity Modelling. In P. Perez and D. Batten, editors, *Complex Science for a Complex World: Exploring Human Ecosystems with Agents*, page 227. Anu E Press, ANU, 2006. URL http://press.anu.edu.au//cs/mobile_devices/ch11s07.html.

BBC. BBC - Douglas Fraser's Ledger: Keeping the lights on, 2010. URL http://www.bbc.co.uk/blogs/thereporters/douglasfraser/2010/03/keeping_the_lights_on.html.

BBC. Solar feed-in tariff cut delayed by government, May 2012. URL http://www.bbc.co.uk/news/business-18192302.

BBC. Smart meter project is delayed. *BBC*, May 2013a. URL http://www.bbc.co.uk/news/business-22480068.

BBC. Only 132 signed up to Green Deal programme, August 2013b. URL http://www.bbc.co.uk/news/business-23766117.

BBC. Drax pulls out of £1bn carbon capture project, September 2015. URL http://www.bbc.co.uk/news/business-34356117.

BBC and Douglas Fraser. Imports to keep the lights on, 2015. URL http://www.bbc.co.uk/news/uk-scotland-scotland-business-32991889.

BBC and Nick Robinson. Can they cut our energy bills and keep the lights on?, 2013. URL http://www.bbc.co.uk/news/uk-politics-25053350.

Ansgar Becker and Dev Team. HeidiSQL, 2013. URL http://www.heidisql.com/.

Henri Bénard. Les tourbillons cellulaires dans une nappe liquide.-Méthodes optiques d'observation et d'enregistrement. *Journal de Physique Théorique et Appliquée*, 10(1):254–266, 1901. URL http://jphystap.journaldephysique.org/articles/jphystap/abs/1901/01/jphystap_1901__10__254_0/jphystap_1901__10__254_0.html.

Sean M. Bergin. Torsten Hägerstrand's Spatial Innovation Diffusion Model (Version 2), September 2012. URL http://www.openabm.org/model/3163/version/2/view.

Noam Bergman. Can micro-generation catalyse behaviour change in the domestic energy sector in the UK? In *Broussous, C. and Jover, C., (eds) Proceedings of the eceee 2009 summer study*, pages 21–32, La Colle sur Loup, France, 2009. ECEEE. URL www.eceee.org/conference_proceedings/eceee/2009/Panel_1/1.029/.

Frans Berkhout. Normative expectations in systems innovation. *Technology Analysis & Strategic Management*, 18(3-4):299–311, July 2006. ISSN 0953-7325. doi: 10.1080/09537320600777010. URL http://dx.doi.org/10.1080/09537320600777010.

Frans Berkhout, Adrian Smith, and Andy Stirling. Socio-technological regimes and transition contexts. *System innovation and the transition to sustainability: theory, evidence and policy. Edward Elgar, Cheltenham*, pages 48–75, 2004.

BMWi. Bundesministerium fur Wirtschaft und Energie (BMWi) - EEG-Reform, 2014. URL http://www.bmwi.de/DE/Themen/Energie/Erneuerbare-Energien/eeg-reform.html.

P. Boait, B.M. Ardestani, and J. Richard Snape. Accommodating renewable generation through an aggregator-focused method for inducing demand side response from electricity consumers. *Renewable Power Generation, IET*, 7(6):689–699, November 2013. ISSN 1752-1416. doi: 10.1049/iet-rpg.2012.0229.

Peter J. Boait and J. Richard Snape. Demand management for isolated mini-grids supplied by renewable generation. In *Developments in Renewable Energy Technology (ICDRET), 2014 3rd International Conference on the*, pages 1–6, Dhaka, Banglasdesh, May 2014. IEEE. doi: 10.1109/ICDRET.2014.6861688.

Eric Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems.

Proceedings of the National Academy of Sciences of the United States of America, 99(Suppl 3): 7280–7287, 2002.

Andy Boston. Delivering a secure electricity supply on a low carbon pathway. *Energy Policy*, 52: 55–59, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.02.004. URL http://www.sciencedirect.com/science/article/pii/S0301421512001000.

P. Bourdieu. *Outline of a Theory of Practice*. Cambridge University Press (first published in French 1973), 1977. ISBN 0-521-29164-X.

J. Bower and D. Bunn. A model-based comparison of pool and bilateral market mechanisms for electricity trading. *Energy Journal*, 21(3):1–29, 2000.

George EP Box and Norman Richard Draper. *Empirical model-building and response surfaces*. Wiley New York, 1987.

M. E. Bratman. *Intention, plans, and practical reason*. Harvard University Press Cambridge, MA, 1987.

Thomas Brenner. Chapter 18: Agent Learning Representation: Advice on Modelling Economic Learning. In L. Tesfatsion and K. L. Judd, editors, *Handbook of computational Economics: Agent-Based Computational Economics*, volume Volume 2, pages 895–947. North-Holland, 2006. ISBN 1574-0021. URL http://www.sciencedirect.com/science/article/B7P5C-4JR414P-7/2/ed71a255aabd7d9a8701ec85f3b92c38.

Maxwell Brown. Catching the PHEVer: Simulating Electric Vehicle Diffusion with an Agent-Based Mixed Logit Model of Vehicle Choice. *Journal of Artificial Societies and Social Simulation*, 16 (2):5, March 2013. ISSN 1460-7425.

Bundesnetzagentur. Increase in the number of photovoltaic systems, September 2012. URL http://www.bundesnetzagentur.de/SharedDocs/Pressemitteilungen/EN/2012/120109IncreaseNumberPhotovoltaicSystems.html.

Jacquelin Burgess and Michael Nye. Re-materialising energy use through transparent monitoring systems. *Energy Policy*, 36(12):4454–4459, December 2008. ISSN 0301-4215. doi: doi:\%0020DOI:\%002010.1016/j.enpol.2008.09.039. URL http://www.sciencedirect.com/science/article/B6V2W-4TRR902-5/2/90bdb8165bac36aed0a42a9b68f198b2.

R. R. Bush and F. Mosteller. *Stochastic models for learning*. John Wiley & Sons, Inc, New York, 1955.

Colin Camerer and Teck Hua Ho. Experience-weighted Attraction Learning in Normal Form Games. *Econometrica*, 67(4):827–874, 1999. ISSN 1468-0262. URL http://dx.doi.org/10.1111/1468-0262.00054.

Sanya Carley. Distributed generation: An empirical analysis of primary motivators. *Energy Policy*, 37(5):1648–1659, May 2009. ISSN 0301-4215. doi: doi:\%0020DOI:\%002010.1016/j.enpol.2009.01.003. URL http://www.sciencedirect.com/science/article/B6V2W-4VMX83S-3/2/844eb09f94be756aef83cd3a756112cf.

Sanya Carley. Historical analysis of U.S. electricity markets: Reassessing carbon lock-in. *Special Section on Offshore wind power planning, economics and environment*, 39(2):720–732, February 2011. ISSN 0301-4215. doi: 10.1016/j.enpol.2010.10.045. URL http://www.sciencedirect.com/science/article/pii/S0301421510007962.

Sanya Carley and Richard N. Andrews. Creating a sustainable U.S. electricity sector: the question of scale. *Policy Sciences*, 45(2):97–121, June 2012. ISSN 00322687. doi: 10.2307/41486858. URL http://www.jstor.org/stable/41486858.

P. Chand, G. Grozev, P. da Silva, and M. Thatcher. Modelling Australia's National Electricity Market using NEMSIM. In *SimTecT 2008 Conference Proceeding*, 2008.

R. Cirillo, P. Thimmapuram, T. Veselka, V. Koritarov, G. Conzelmann, Charles M. Macal, G. Boyd, M. North, T. Overbye, and X. Cheng. Evaluating the potential impact of transmission constraints on the operation of a competitive electricity market in Illinois. Technical Report ANL-06/16, Argonne National Laboratory (ANL), 30th April 2006. URL http://www.osti.gov/bridge/servlets/purl/925314-ICyPVp/.

Duncan Clark. Feed-in tariffs cuts cast solar future in a new light. *The Guardian*, June 2011. ISSN 0261-3077. URL http://www.theguardian.com/environment/2011/jun/10/feed-in-tariffs-solar.

Commons Library. Smart meters - Commons Library Standard Note - UK Parliament. Commons

Library - Standard Note SN06179, Commons Library, London, June 2013. URL http://www.parliament.uk/briefing-papers/SN06179.

Consumer Focus. What's in it for me? – Using the benefits of energy efficiency to overcome the barriers. Technical report, June 2012. URL http://www.consumerfocus.org.uk/publications/whats-in-it-for-me-using-the-benefits-of-energy-efficiency-to-overcome-the-barriers.

Matthew Cook and Per-Anders Langendahl. Transport and Energy Use. *The SAGE Handbook of Transport Studies*, page 397, 2013.

S. Darby. The effectiveness of feedback on energy consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays*, 486, 2006.

Edward Davey and DECC. Written Ministerial Statement by Edward Davey: Smart Metering, October 2013. URL https://www.gov.uk/government/speeches/written-ministerial-statement-by-edward-davey-smart-metering.

DECC. Impact Assessment of Feed-in Tariffs for Small-Scale, Low Carbon, Electricity Generation. Impact Assessment URN: 09D/703, Department of Energy and Climate Change, London, July 2009. URL http://www.fitariffs.co.uk/FITs/detailed/.

DECC. 2050 Pathways Calculator, 2010a. URL http://2050-calculator-tool.decc.gov.uk/pathways/.

DECC. Consultation on Electricity Market Reform. Technical report, Department for Energy and Climate Change (DECC), London, December 2010b. URL http://www.decc.gov.uk/en/content/cms/consultations/emr/emr.aspx.

DECC. Sub-national energy consumption statistics - Department of Energy and Climate Change (archived), 2010c. URL http://webarchive.nationalarchives.gov.uk/20130109092117/http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/regional/regional.aspx.

DECC. 2050 Pathways Analysis. Technical report, Department for Energy and Climate Change (DECC), London, July 2010d. URL http://www.decc.gov.uk/en/content/cms/what_we_do/lc_uk/2050/2050.aspx.

DECC. Smart Meters Implementation Programme: delivery plan, December 2011a. URL http://www.decc.gov.uk/en/content/cms/tackling/smart_meters/smart_meters.aspx.

DECC. Sub-national electricity consumption data. Government statistics, DECC, London, 2011b. URL http://webarchive.nationalarchives.gov.uk/20130109092117/http://decc.gov.uk/en/content/cms/statistics/energy_stats/regional/electricity/electricity.aspx.

DECC. My2050, March 2011c. URL http://my2050.decc.gov.uk/.

DECC. Solar PV cost controls comprehensive review (Phase 2A) - Consultations, 2012. URL https://www.gov.uk/government/consultations/solar-pv-cost-controls-comprehensive-review-phase-2a.

DECC. Domestic RHI Impact Assessment. Impact Assessment IA No: DECC0099, Department for Energy and Climate Change (DECC), London, July 2013a. URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/211978/Domestic_RHI_Impact_Assessment.pdf.

DECC. Domestic energy fact file and housing surveys, January 2013b. URL https://www.gov.uk/government/organisations/department-of-energy-climate-change/series/domestic-energy-fact-file-and-housing-surveys#publications.

DECC. The future of heating: meeting the challenge. Technical report, Department for Energy and Climate Change (DECC), London, UK, March 2013c. URL https://www.gov.uk/government/publications/the-future-of-heating-meeting-the-challenge.

DECC. Changes to green home improvement policies announced today, July 2015a. URL https://decc.blog.gov.uk/2015/07/23/changes-to-green-home-improvement-policies-announced-today/.

DECC. Monthly feed-in tariff commissioned installations by month, 2015b. URL https://www.gov.uk/government/statistics/monthly-small-scale-renewable-deployment.

DECC. Consultation on a review of the Feed-in Tariff scheme, August 2015c. URL https://www.gov.uk/government/consultations/consultation-on-a-review-of-the-feed-in-tariff-scheme.

DECC. Solar photovoltaics deployment statistics, 2015d. URL https://www.gov.uk/government/statistics/solar-photovoltaics-deployment.

DECC. More community energy projects to get support under Feed-in Tariffs - Press release. *Press notice: 13/069*, 3rd July 2013. URL https://www.gov.uk/government/news/more-community-energy-projects-to-get-support-under-feed-in-tariffs.

DECC. Green Deal pioneers step forward - Department of Energy and Climate Change, 4/4/12. URL http://www.decc.gov.uk/en/content/cms/news/pn12_042/pn12_042.aspx.

DEFRA. A Framework for pro-environmental behaviours. Technical report, Department for Environment, Farming and Rural Affairs, UK Government, London, January 2008. URL http://www.defra.gov.uk/evidence/social/behaviour/.

Alexey Dolgachov. DBFNavigator: Viewer and Editor DBF tables, 2002. URL http://www.alxsoft.narod.ru/.

R. E. Dunlap and K. D. Van Liere. A Proposed Measuring Instrument and Preliminary Results: The 'New Environmental Paradigm.'. *Journal of Environmental Education*, 9:10–19, 1978.

Bruce Edmonds. Simplicity is not truth-indicative. *Philosophy and complexity*, pages 65–80, 2007.

Bruce Edmonds and Scott Moss. From KISS to KIDS – An 'Anti-simplistic' Modelling Approach. In Paul Davidsson, Brian Logan, and Keiki Takadama, editors, *Multi-Agent and Multi-Agent-Based Simulation*, volume 3415 of *Lecture Notes in Computer Science*, pages 130–144. Springer Berlin Heidelberg, January 2005. ISBN 978-3-540-25262-7. URL http://dx.doi.org/10.1007/978-3-540-32243-6_11.

Corinna Elsenbroich and Nigel Gilbert. Agent-Based Modelling. In *Modelling Norms*, pages 65–84. Springer, 2014. ISBN 94-007-7051-0. URL http://books.google.co.uk/books?id=4dVEAAAAQBAJ.

ENSG. Electricity Networks Strategy Group - A Smart Grid Routemap. Technical report, ENSG, United Kingdom, February 2010. URL http://webarchive.nationalarchives.gov.uk/20100919181607/http://www.ensg.gov.uk/assets/ensg_routemap_final.pdf.

J. M. Epstein. Why Model? *Journal of Artificial Societies and Social Simulation*, 11(4):12, October 2008. URL http://jasss.soc.surrey.ac.uk/11/4/12.html#feynman1999.

J. M. Epstein and Robert Axtell. *Growing Artificial Societies - Social Science from the Bottom Up*. MIT Press, Cambridge, MA, 1996.

(Energy Saving Trust) EST. Solar electricity PV (photovoltaic) panels explained - benefits, costs, savings, earnings, suitability, 2012. URL http://www.energysavingtrust.org.uk/Generating-energy/Choosing-a-renewable-technology/Solar-panels-PV.

Energy Saving Trust EST. Solar panels | Energy Saving Trust, 2015. URL http://www.energysavingtrust.org.uk/domestic/solar-panels.

ETP. Definition - SmartGrids: European Technology Platform for the Electricity Networks of the Future, 2006. URL http://www.smartgrids.eu/ETPSmartGrids.

EurActiv. Cameron pledges review of green energy tariffs, October 2013. URL http://www.euractiv.com/eu-elections-2014/cameron-pledges-review-green-ene-news-531270. UK Prime Minister David Cameron has pledged to roll back the £112 annual costs of green tariffs on energy bills, as he came under fire over Sir John Major's call for a windfall tax on the excess profits of Britain's big six energy companies.

European Union (EU). On the effort of Member States to reduce their greenhouse gas emissions to meet the Community's greenhouse gas emission reduction commitments up to 2020, April 2009a.

European Union (EU). On the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, April 2009b.

European Union (EU). A Roadmap for moving to a competitive low carbon economy in 2050, 2011.

European Union (EU). On energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/EC and 2006/32/EC, October 2012.

European Union (EU). 2030 climate & energy framework - European Commission, 2014. URL http://ec.europa.eu/clima/policies/strategies/2030/documentation_en.htm.

EWCA Civ 28. Secretary of State for Energy and Climate Change v Friends of the Earth & Ors [2012] EWCA Civ 28, January 2012. URL http://www.bailii.org/ew/cases/EWCA/Civ/2012/28.html.

A. Faruqui and S. George. Quantifying customer response to dynamic pricing. *The Electricity Journal*, 18(4):53–63, 2005.

A. Faruqui and S. Sergici. Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulatory Economics*, 38(2):193–225, 2010.

A. Faruqui, S. Sergici, and A. Sharif. The impact of informational feedback on energy consumption–A survey of the experimental evidence. *Energy*, 35(4):1598–1608, 2010.

Ahmad Faruqui. Chapter 3 - The Ethics of Dynamic Pricing. In Fereidoon P. Sioshansi, editor, *Smart Grid*, pages 61–83. Academic Press, Boston, 2012. ISBN 978-0-12-386452-9. URL http://www.sciencedirect.com/science/article/pii/B9780123864529000036.

Ahmad Faruqui, Ryan Hledik, Sam Newell, and Hannes Pfeifenberger. The Power of 5 Percent. *The Electricity Journal*, 20(8):68–77, October 2007. ISSN 1040-6190. doi: 10.1016/j.tej.2007.08.003. URL http://www.sciencedirect.com/science/article/pii/S1040619007000991.

P. Favre-Perrod, R. Critchley, E. Catz, and M. Bazargan. New participants in SmartGrids and associated challenges in the transition towards the grid of the future. *PowerTech, 2009 IEEE Bucharest*, pages 1–5, 2009. doi: 10.1109/PTC.2009.5281828.

Foresight. Foresight Sustainable Energy Management and the Built Environment Project. Final project report 140-08-FO/B, The Government Office for Science, London, 2008. URL http://bis.ecgroup.net/Publications/Foresight/SustainableEnergyManagementBuiltEnvironment.aspx.

Office of Science Foresight and Technology. Intelligent Infrastructure Futures: The Scenarios - Towards 2055. Technical report, Office of Science and Technology, London, 2006. URL http://www.bis.gov.uk/assets/foresight/docs/intelligent-infrastructure-systems/the-scenarios-2055.pdf.

Roger Fouquet and Peter J.G. Pearson. Past and prospective energy transitions: Insights from history. *Energy Policy*, 50:1–7, November 2012. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.08.014. URL http://www.sciencedirect.com/science/article/pii/S0301421512006805.

Timothy J. Foxon. Transition pathways for a UK low carbon electricity future. *Energy Policy*, 52(0):10–24, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.04.001. URL http://www.sciencedirect.com/science/article/pii/S0301421512002868.

Timothy J. Foxon, Geoffrey P. Hammond, and Peter J.G. Pearson. Developing transition pathways for a low carbon electricity system in the UK. *Technological Forecasting and Social Change*, 77(8):1203–1213, October 2010. ISSN 0040-1625. doi: doi:\%002010.1016/j.techfore.2010.04.002. URL http://www.sciencedirect.com/science/article/pii/S0040162510000697.

Timothy J. Foxon, Peter J.G. Pearson, Stathis Arapostathis, Anna Carlsson-Hyslop, and Judith Thornton. Branching points for transition pathways: assessing responses of actors to challenges on pathways to a low carbon future. *Energy Policy*, 52:146–158, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.04.030. URL http://www.sciencedirect.com/science/article/pii/S0301421512003308.

Frontier Economics and Sustainability First. Demand Side Response in the domestic sector- a literature review of major trials. Technical Report 12D/257, Department for Energy and Climate Change (DECC), London, August 2012. URL http://www.frontier-economics.com/_library/publications/Frontier%20Paper%20-%20Demand%20side%20response%20in%20the%20domestic%20sector.pdf.

Chin Kim Gan, M. Aunedi, V. Stanojevic, Goran Strbac, and D. Openshaw. Investigation of the Impact of Electrifying Transport and HeatSectors on the UK Distribution Networks. In *Proceedings of CIRED 2011*, Frankfurt, 2011. URL https://sites.google.com/site/ganchinkim/CIRED2011_0710_FINAL.pdf?attredirects=0.

Rosanna Garcia. Uses of Agent Based Modeling in Innovation/New Product Development Research. *Journal of Product Innovation Management*, 22(5):380–398, 2005.

F. W. Geels. Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy*, 31(8-9):1257–1274, 2002. URL http://www.sciencedirect.com/science?_ob=ArticleURL&_udi=B6V77-45Y01M2-8&_user=698911&_coverDate=12%2F31%2F2002&_rdoc=4&_fmt=high&_orig=browse&_origin=browse&_zone=rslt_list_item&_srch=doc-info%28%23toc%235835%232002%23999689991%23367883%23FLA%23display%23Volume%29&_cdi=5835&_sort=d&_docanchor=&_ct=24&_acct=C000039118&_version=1&_urlVersion=0&_userid=698911&md5=c6907cff6eff6dcad48bdc1872e8e65a&searchtype=a.

F. W. Geels. *Technological transitions and system innovations: a co-evolutionary and socio-technical analysis*. Edward Elgar Publishing, 2005. ISBN 1-84542-009-8.

F. W. Geels. Ontologies, socio-technical transitions (to sustainability), and the multi-level perspective. *Research Policy*, 39(4):495–510, May 2010. ISSN 0048-7333. doi: doi:\%0020DOI:\%002010.1016/j.respol.2010.01.022.

F. W. Geels and J. Schot. Typology of sociotechnical transition pathways. *Research Policy*, 36(3):399–417, April 2007. ISSN 0048-7333. doi: doi:\%0020DOI:\%002010.1016/j.respol.2007.01.003. URL http://www.sciencedirect.com/science/article/B6V77-4N3GNND-2/2/f9e4202b77fbd645d5e8eab6a26400a0.

Frank W. Geels. The multi-level perspective on sustainability transitions: Responses to seven criticisms. *Environmental Innovation and Societal Transitions*, 1(1):24–40, June 2011. ISSN 2210-4224. doi: 10.1016/j.eist.2011.02.002. URL http://www.sciencedirect.com/science/article/pii/S2210422411000050.

Frank W. Geels. A socio-technical analysis of low-carbon transitions: introducing the multi-level perspective into transport studies. *Journal of Transport Geography*, 24:471–482, September 2012. ISSN 0966-6923. doi: 10.1016/j.jtrangeo.2012.01.021. URL http://www.sciencedirect.com/science/article/pii/S0966692312000269.

F.W. Geels. The impact of the financial-economic crisis on sustainability transitions: Financial investment, governance and public discourse. *Environmental Innovation and Societal Transitions*, 6:67–95, March 2013. ISSN 22104224. doi: 10.1016/j.eist.2012.11.004. URL http://www.sciencedirect.com/science/article/pii/S221042241200069X.

A. Genus and A. M Coles. A Critique of Geels' Multi-level Perspective of Technological Transition.

International Summer Academy on Technology Studies-Transforming the Energy System. Graz, IFZ, 2007.

A. Genus and A. M Coles. Rethinking the multi-level perspective of technological transitions. *Research policy*, 37(9):1436–1445, 2008.

Anthony Giddens. *The constitution of society: introduction of the theory of structuration*. Univ of California Press, 1984. ISBN 0-520-05292-7.

G. N. Gilbert. *Agent-based models*. Sage Publications, Inc, London, 2008. ISBN 1-4129-4964-5.

John Glassmire, Paul Komor, and Peter Lilienthal. Electricity demand savings from distributed solar photovoltaics. *Renewable Energy in China*, 51(0):323–331, December 2012. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.08.022. URL http://www.sciencedirect.com/science/article/pii/S0301421512007045.

General Register Office for Scotland GRO Scotland. 2001 Census: Digitised Boundary Data (Scotland) [computer file]. UK Data Service Census Support. Downloaded from: http://edina.ac.uk/census, 2001a. URL www.edina.ac.uk/census.

General Register Office for Scotland GRO Scotland. 2001 Census: Aggregate Data (Scotland) [computer file]. UK Data Service Census Support. Downloaded from: http://casweb.mimas.ac.uk, 2001b. URL casweb.mimas.ac.uk.

Arnulf Grubler, Thomas B. Johansson, Luis Mundaca, Nebojsa Nakicenovic, Shonali Pachauri, Keywan Riahi, Hans-Holger Rogner, and Lars Strupeit. Chapter 1 - Energy Primer. In *Global Energy Assessment - Toward a Sustainable Future*, pages 99–150. Cambridge University Press, Cambridge University Press, Cambridge, UK and New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria, 2012. ISBN 9781 10700 5198 hardback 9780 52118 2935 paperback. URL www.globalenergyassessment.org.

Philipp H. Grünewald, Timothy T. Cockerill, Marcello Contestabile, and Peter J.G. Pearson. The socio-technical transition of distributed electricity storage into future networks—System value and stakeholder views. *Energy Policy*, 50:449–457, November 2012. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.07.041. URL http://www.sciencedirect.com/science/article/pii/S0301421512006337.

Guardian. David Cameron at centre of 'get rid of all the green crap' storm. *The Guardian*, November 2013. URL http://www.theguardian.com/environment/2013/nov/21/david-cameron-green-crap-comments-storm.

E. Guerci, S. Ivaldi, M. Raberto, and S. Cincotti. Learning Oligopolistic competition in electricity auctions. *Computational Intelligence*, 23(2):197–220, 2007. ISSN 1467-8640. URL http://dx.doi.org/10.1111/j.1467-8640.2007.00298.x.

E. Guerci, Stefano Ivaldi, and Silvano Cincotti. Learning Agents in an Artificial Power Exchange: Tacit Collusion, Market Power and Efficiency of Two Double-auction Mechanisms. *Computational Economics*, 32(1):73–98, September 2008a. ISSN 0927-7099. URL http://dx.doi.org/10.1007/s10614-008-9127-5.

E. Guerci, M. A. Rastegar, S. Cincotti, F. Delfino, R. Procopio, and M. Ruga. Supply-side gaming on electricity markets with physical constrained transmission network. In *Electricity Market, 2008. EEM 2008. 5th International Conference on European*, pages 1–6. IEEE, 2008b.

Pedro Guertler. Somewhere between a 'Comedy of errors' and 'As you like it'? A brief history of Britain's 'Green Deal' so far. In *Proceedings of Renew, Rethink, Refresh - ECEEE Summer Study 2013*, Presqui'ile des Giens, France, 2013. ECEEE. URL http://www.ukace.org/wp-content/uploads/2013/06/1-306-13_Guertler.pdf.

Torsten Hägerstrand. A Monte Carlo approach to diffusion. *European Journal of Sociology*, 6(1):43–67, 1965.

Lynne Hamill and Nigel Gilbert. Social Circles: A Simple Structure for Agent-Based Social Network Models, March 2009. URL http://jasss.soc.surrey.ac.uk/12/2/3.html. None of the standard network models fit well with sociological observations of real social networks. This paper presents a simple structure for use in agent-based models of large social networks. Taking the idea of social circles, it incorporates key aspects of large social networks such as low density, high clustering and assortativity of degree of connectivity. The model is very flexible and can be used to create a wide variety of artificial social worlds.

D. J. Hamilton, W. J. Nuttall, and F. A. Roques. Agent based simulation of technology adoption. Working Paper 0923, University of Cambridge, Energy Policy Research Group, Cambridge, England, 2009. URL http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.392.2231&rep=rep1&type=pdf.

Geoffrey P. Hammond and Peter J.G. Pearson. Challenges of the transition to a low carbon, more electric future: From here to 2050. *Energy Policy*, 52:1–9, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.10.052. URL http://www.sciencedirect.com/science/article/pii/S0301421512009378.

Hansard. House of Commons Debates for 10 Feb 2011 Column 455. October 2011. URL http://www.publications.parliament.uk/pa/cm201011/cmhansrd/cm110210/debtext/110210-0001.htm.

Hansard. House of Commons Debates for 26 Jan 2012 Column 399. January 2012. URL http://www.publications.parliament.uk/pa/cm201212/cmhansrd/cm120126/debtext/120126-0001.htm.

Tom Hargreaves, Michael Nye, and Jacquelin Burgess. Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy*, 38(10):6111–6119, October 2010. ISSN 0301-4215. doi: doi:\%002010.1016/j.enpol.2010.05.068. URL http://www.sciencedirect.com/science/article/pii/S030142151000460X.

Tom Hargreaves, Alex Haxeltine, Noel Longhurst, and Gill Seyfang. Sustainability transitions from the bottom-up: Civil society, the multi-level perspective and practice theory. Technical Report 2011-01, Norwich: CSEGRE, 2011. URL http://www.econstor.eu/handle/10419/48796.

Fiona Harvey and environment correspondent. Solar companies take legal action over UK feed-in tariff cuts. *The Guardian*, April 2011. ISSN 0261-3077. URL http://www.theguardian.com/environment/2011/apr/19/solar-legal-action-feed-in-tariffs.

A. Haxeltine, L. Whitmarsh, N. Bergman, J. Rotmans, M. Schilperoord, and J. Kohler. A Conceptual Framework for transition modelling. *International journal of innovation and sustainable development*, 3(1):93–114, 2008.

Andrew Higgins, Phillip Paevere, John Gardner, and George Quezada. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. *Technological Forecasting and Social Change*, 79(8):1399–1412, October 2012. ISSN 0040-1625. doi: 10.1016/j.techfore.2012.04.008. URL http://www.sciencedirect.com/science/article/pii/S0040162512000972.

Georg Holtz. Modelling transitions: An appraisal of experiences and suggestions for research. *Environmental Innovation and Societal Transitions*, 1(2):167–186, December 2011. ISSN 2210-4224. doi: 10.1016/j.eist.2011.08.003. URL http://www.sciencedirect.com/science/article/pii/S2210422411000335.

Nick Hughes and Neil Strachan. Methodological review of UK and international low carbon scenarios. *The socio-economic transition towards a hydrogen economy - findings from European research, with regular papers*, 38(10):6056–6065, October 2010. ISSN 0301-4215. doi: 10.1016/j.enpol.2010.05.061. URL http://www.sciencedirect.com/science/article/pii/S0301421510004325.

Integovernmental Panel on Climate Change IPCC. Climate Change 2013: The Physical Science Basis - Working Group I contribution to Assessment Report 5 (AR5). Technical report, IPCC, 2013.

Integovernmental Panel on Climate Change IPCC. Impacts, adaptation and vulnerability - Working Group II contribution to Assessment Report 5 (AR5). Technical report, IPCC, Yokohama, March 2014.

T. Jackson. Motivating Sustainable Consumption: a Review of Evidence on Consumer Behaviour and Behavioural Change: a Report to the Sustainable Development Research Network. Technical report, Centre for Environmental Strategy, University of Surrey, 2005. URL www.c2p2online.com/documents/MotivatingSC.pdf.

Wander Jager. Stimulating the diffusion of photovoltaic systems: A behavioural perspective. *Energy Policy*, 34(14):1935–1943, September 2006. ISSN 0301-4215. doi: 10.1016/j.enpol.2004.12.022. URL http://www.sciencedirect.com/science/article/pii/S0301421505000248.

M. A. Janssen and W. Jager. An integrated approach to simulating behavioural processes: A case study of the lock-in of consumption patterns. *Journal of Artificial Societies and Social Simulation*, 2(2), 31st march 1999. URL http://jasss.soc.surrey.ac.uk/2/2/2.html.

R. Kemp, J. Schot, and R. Hoogma. Regime shifts to sustainability through processes of niche formation: the approach of strategic niche management. *Technology Analysis & Strategic Management*, 10(2):175–198, 1998.

Elmar Kiesling, Markus Günther, Christian Stummer, and Lea M. Wakolbinger. Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, 20(2):183–230, 2012. doi: 10.1007/s10100-011-0210-y. URL https://www.researchgate.net/publication/225831322_Agent-based_simulation_of_innovation_diffusion_A_review.

D. Koesrindartoto, J. Sun, and L. Tesfatsion. An agent-based computational laboratory for testing the economic reliability of wholesale power market designs. In *Proceedings of the IEEE Power and Energy Society General Meeting*, pages 931–936, San Francisco, California, June 2005.

J. K. Kok, C. J. Warmer, and I. G. Kamphuis. PowerMatcher: multiagent control in the electricity infrastructure. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, pages 75–82. ACM, 2005. ISBN 1-59593-093-0.

J. K. Kok, C. Warmer, and R. Kamphuis. The PowerMatcher: Multiagent control of electricity demand and supply. *IEEE Intelligent Systems*, 21(2):89–90, 2006.

J. K. Kok, M.J.J. Scheepers, and I.G. Kamphuis. Intelligence in Electricity Networks for Embedding Renewables and Distributed Generation. In Rudy Negenborn, Zofia Lukszo, and Hans Hellendoorn, editors, *Intelligent Infrastructures*. Springer, 2010. ISBN 978-90-481-3597-4.

Bruno Latour. *Science in action: How to follow scientists and engineers through society*. Harvard university press, 1987. ISBN 0-674-79291-2.

Bruno Latour. Where are the missing masses? The sociology of a few mundane artifacts. In Wiebe E. Bijker and John Law, editors, *Shapint Technology/Building Sociey: Studies in Sociotechnical Change*, pages 225–258. MIT Press, Cambridge, MA, author reprint (web) edition, 1992.

Claudia Leepa and Matthias Unfried. Effects of a cut-off in feed-in tariffs on photovoltaic capacity: Evidence fromGermany. *Energy Policy*, 56(0):536 – 542, 2013. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2013.01.018. URL http://www.sciencedirect.com/science/article/pii/S0301421513000256.

Phillip A. Leicester, Chris I. Goodier, and Paul Rowley. Evaluating the impacts of community renewable energy initiatives. In *Proceedings of the ISES Solar World Congress 2011*, Kassel, Germany, August 2011. International Solar Energy Society. URL https://dspace.lboro.ac.uk/dspace-jspui/handle/2134/9185. This is a conference paper.

Kurt Lewin. *Field theory in social science: selected theoretical papers.* Harpers, 1951. URL http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=1951-06769-000&site=ehost-live.

H. Li and L. Tesfatsion. ISO Net Surplus Collection and Allocation in Wholesale Power Markets under LMP. *Staff General Research Papers*, 2009.

N. W. A. Lidula and A. D. Rajapakse. Microgrids research: A review of experimental microgrids and test systems. *Renewable and Sustainable Energy Reviews*, 15(1):186–202, 2011.

William Lilley, Jennifer Hayward, and Luke Reedman. Chapter 7 - Realizing the Potential of Renewable and Distributed Generation. In Fereidoon P. Sioshansi, editor, *Smart Grid*, pages 161–183. Academic Press, Boston, 2012. ISBN 978-0-12-386452-9. URL http://www.sciencedirect.com/science/article/pii/B9780123864529000073.

Charles M. Macal, Easan Drury, Diane J. Graziano, Mackay Miller, Jonathan Ozik, and Tod Perry. A Behavior-Based Agent Model for Assessing Market Adoption of Solar Photovoltaics, December 2011. URL http://www.youtube.com/watch?v=GqdLj83keII.

David J.C. MacKay. *Sustainable Energy - without the hot air.* UIT Cambridge, 2008. ISBN 978-0-9544529-3-3. URL www.withouthotair.com.

V. Mahajan, E. Muller, and Frank M. Bass. Diffusion of new products: Empirical generalizations and managerial uses. *Marketing Science*, 14(3 supplement):G79–G88, 1995.

MapWindow GIS Team. MapWindow Programmable Geographic Information System (v4.8.6), November 2011. URL www.mapwindow.org.

Bertha Maya Sopha, Christian A. Klöckner, and Edgar G. Hertwich. Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. *Energy Policy*, 39(5):2722–2729, May 2011. ISSN 0301-4215. doi: 10.1016/j.enpol.2011.02.041. URL http://www.sciencedirect.com/science/article/pii/S0301421511001315.

MBizon. Electricity Grid Schematic English, March 2010. URL http://commons.wikimedia.org/wiki/File:Electricity_Grid_Schematic_English.svg.

Matt McGrath and BBC. Subsidies for small scale solar face steep cuts, August 2015. URL http://www.bbc.co.uk/news/science-environment-34073541.

MCS. Microgeneration Certification Scheme - FAQs - Consumers, 2013. URL http://www.microgenerationcertification.org/about-us/faqs/faqs-consumers#no4.

James Meadowcroft. Engaging with the politics of sustainability transitions. *Environmental Innovation and Societal Transitions*, 1(1):70–75, June 2011. ISSN 22104224. doi: 10.1016/j.eist.2011.02.003. URL http://linkinghub.elsevier.com/retrieve/pii/S2210422411000074.

J. Michaelis, F. Genoese, and M. Wietschel. Evaluation of Large Scale Hydrogen Storage Systems in the German Energy Sector. *Fuel Cells*, 14(3):517–524, 2014.

J. H. Miller and S. E. Page. *Complex adaptive systems: An introduction to computational models of social life*. Princeton Univ Pr, 2007. ISBN 0-691-13096-5.

Nigel Morris. Thousands of jobs at risk after David Cameron abandons solar subsidies. *The Independent*, May 2012. URL http://www.independent.co.uk/news/uk/politics/thousands-of-jobs-at-risk-after-david-cameron-abandons-solar-subsidies-7718665.html.

Firdaus Muhammad-Sukki, Roberto Ramirez-Iniguez, Abu Bakar Munir, Siti Hajar Mohd Yasin, Siti Hawa Abu-Bakar, Scott G. McMeekin, and Brian G. Stewart. Revised feed-in tariff for solar photovoltaic in the United Kingdom: A cloudy future ahead? *Energy Policy*, 52:832–838, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.09.062. URL http://www.sciencedirect.com/science/article/pii/S0301421512008440.

Tomoyuki Murakami. Agent-based simulations of the influence of social policy and neighboring communication on the adoption of grid-connected photovoltaics. *Energy Conversion and Management*, 80:158–164, April 2014. ISSN 0196-8904. doi: 10.1016/j.enconman.2014.01.033. URL http://www.sciencedirect.com/science/article/pii/S0196890414000776.

James Murray and Jessica Shankleman. Feed-in tariff future in doubt as government moves to slash renewable energy incentives, August 2015. URL http://www.businessgreen.com/bg/news/2423639/feed-in-tariff-future-in-doubt-as-government-moves-to-slash-renewable-energy-incentiv

National Grid. Solar PV briefing note for DECC, 2012. URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/66609/7335-national-grid-solar-pv-briefing-note-for-decc.pdf.

National Grid. Future Energy Scenarios, October 2013. URL http://www2.nationalgrid.com/uk/industry-information/future-of-energy/fes/Documents/.

R. R. Nelson and S. G. Winter. *An evolutionary theory of economic change*. Belknap Press, 1982. ISBN 0-674-27228-5.

J. Nicolaisen, V. Petrov, and L. Tesfatsion. Market power and efficiency in a computational electricity market with discriminatory double-auction pricing. *IEEE Transactions on Evolutionary Computation*, 5(5):504–523, October 2001. ISSN 1089778X. doi: 10.1109/4235.956714. URL http://ieeexplore.ieee.org/xpl/downloadCitations.

G. Nicolis and I. Prigogine. *Exploring complexity: An introduction*. W.H Freeman and company, New York, 1989. ISBN 0-7167-1859-6.

Gregoire Nicolis and Ilya Prigogine. *Self-organization in nonequilibrium systems*. John Wiley & Sons, Brussels, 1977.

M. North, C. Macal, G. Conzelmann, V. Koritarov, P. Thimmapuram, and T. Veselka. Multi-agent electricity market modeling with EMCAS. In *Computational Analysis of Social and Organizational Science Conference*, Pittsburgh, PA (US), June 2002.

M. North, P. Thimmapuram, R. Cirillo, C. Macal, G. Conzelmann, V. Koritarov, and T. Veselka. EMCAS: An agent-based tool for modeling electricity markets. *Agent 2003: Challenges in Social Simulation*, 2003.

John A. Norton and Frank M. Bass. A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. *Management Science*, 33(9):1069–1086, January 1987. ISSN 0025-1909, 1526-5501. doi: 10.1287/mnsc.33.9.1069. URL http://mansci.journal.informs.org/content/33/9/1069.

W. J. Nuttall, T. Zhang, D. J. Hamilton, and F. A. Roques. Sociophysics Simulations of Technology Adoption and Consumer Behavior. In *Proceedings of the Second International Symposium on Engineering Systems*, page 12, Cambridge, MA, June 2009. MIT. URL https://esd.mit.edu/symp09/submitted-papers/nuttall-paper.pdf.

M. Nye, L. Whitmarsh, and T. J. Foxon. Socio-psychological perspectives on the active roles of domestic actors in transition to a lower carbon electricity economy. *Environment and Planning A*, 42(3):697–714, 2010.

Ofgem. Feed-in Tariff: Guidance for renewable installations (Version 5). Guidance note 57/13, Ofgem, London, 19th April 2013. URL http://www.ofgem.gov.uk/Sustainability/Environment/fits/Documents1/FIT%20Generator%20Guidance.pdf.

Ofgem. Long-Term Electricity Network Scenarios (LENS) - final report. Final 157/08, Ofgem, London, November 2008. URL http://www.ofgem.gov.uk/Pages/MoreInformation.aspx?docid=5&refer=Networks/Trans/Archive/ElecTrans/LENS.

Ofgem. Electricity Capacity Assessment 2012, October 2012. URL https://www.ofgem.gov.uk/publications-and-updates/electricity-capacity-assessment-2012.

Ofgem. Feed-in Tariff scheme, 2013a. URL http://www.ofgem.gov.uk/Sustainability/Environment/fits/Pages/fits.aspx.

Ofgem. Feed-in Tariff Installation Report (30th June 2013), 2013b. URL http://www.ofgem.gov.uk/Pages/MoreInformation.aspx?docid=51&refer=Sustainability/Environment/fits.

Ofgem. Feed-in Tariff Installation Report (31st March 2013), 2013c. URL http://www.ofgem.gov.uk/Pages/MoreInformation.aspx?docid=49&refer=Sustainability/Environment/fits.

Ofgem. Retail Market Review, 2013d. URL http://www.ofgem.gov.uk/Markets/RetMkts/rmr/Pages/rmr.aspx.

Ofgem. Security of Supply report 2015, July 2015. URL https://www.ofgem.gov.uk/publications-and-updates/electricity-security-supply-report.

Oil Drum. The Oil Drum | World Energy Consumption Since 1820 in Charts, March 2012. URL http://www.theoildrum.com/node/9023.

Office for National Statistics ONS. 2001 Census boundary data: Lookup tables: Postode Headcounts downloaded from http://borders.edina.ac.uk/html/boundary.html, 2001a. URL http://census.ukdataservice.ac.uk/get-data/boundary-data.aspx.

Office for National Statistics ONS. 2001 Census: Digitised Boundary Data (England and Wales) [computer file]. UK Data Service Census Support. Downloaded from: http://edina.ac.uk/census, 2001b. URL www.edina.ac.uk/census.

Office for National Statistics ONS. 2001 Census: Aggregate Data (England and Wales) [computer file]. UK Data Service Census Support. Downloaded from: http://casweb.mimas.ac.uk, 2001c. URL casweb.mimas.ac.uk.

Office for National Statistics ONS. Changes to census geography 2001-2011, January 2013. URL http://www.ons.gov.uk/ons/guide-method/geography/products/census/lookup/2001-2011/index.html.

David Openshaw. Low Carbon London: A smarter approach to managing London's electricity demand - involving customers and communities. In *HEAT & SHIFT Conference Expo*, Cambridge, February 2010. Low Carbon London. URL http://www.cir-strategy.com/uploads/Openshaw.pdf.

Ordnance Survey, GB. OS Code-Point with Polygons [Shapefile geospatial data], Coverage:UK, 2010. URL http://edina.ac.uk/digimap.

Javier Esparza Peidro, Francesc D. Muñoz-Escoí, Luis Irún-Briz, and José M. Bernabéu-Aubán. RJDBC: A Simple Database Replication Engine. In *ICEIS (1)*, pages 587–590, 2004.

Stefan Pfenninger, Adam Hawkes, and James Keirstead. Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, 33:74–86, May 2014. ISSN 1364-0321. doi: 10.1016/j.rser.2014.02.003. URL http://www.sciencedirect.com/science/article/pii/S1364032114000872.

Glenn Platt, Adam Berry, and David Cornforth. Chapter 8 - What Role for Microgrids? In Fereidoon P. Sioshansi, editor, *Smart Grid*, pages 185–207. Academic Press, Boston, 2012. ISBN 978-0-12-386452-9. URL http://www.sciencedirect.com/science/article/pii/B9780123864529000085.

PowerWorld corporation. Simulator Overview » PowerWorld, 2013. URL http://www.powerworld.com/products/simulator/overview.

Python Software Foundation PSF. Python Language (version 2.7.2), June 2011. URL www.python.org/download/releases/2.7.2/.

D. Pudjianto, C. Ramsay, and Goran Strbac. Virtual power plant and system integration of distributed energy resources. *Renewable Power Generation, IET*, 1(1):10–16, 2007.

Danny Pudjianto, Predrag Djapic, Marko Aunedi, Chin Kim Gan, Goran Strbac, Sikai Huang, and David Infield. Smart control for minimizing distribution network reinforcement cost due to electrification. *Energy Policy*, 52:76–84, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.05.021. URL http://www.sciencedirect.com/science/article/pii/S0301421512004338.

PV-Tech. Spanish fines for self-consumption double that for leaking radioactive waste | PV-Tech. *PV-Tech*, June 2015. URL http://www.pv-tech.org/news/spain_proposes_sun_tax_on_storage_of_self_consumption_solar.

Rainer Quitzow, Rainer Walz, Jonathan Köhler, and Klaus Rennings. The concept of "lead markets" revisited: Contribution to environmental innovation theory. *Global Diffusion of Environmental Innovations*, 10(0):4–19, March 2014. ISSN 2210-4224. doi: 10.1016/j.eist.2013.11.002. URL http://www.sciencedirect.com/science/article/pii/S2210422413000890.

R Core Team. R: A Language and Environment for Statistical Computing, 2013. URL http://www.R-project.org.

K. U Rao and V. V. N. Kishore. A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews*, 14(3):1070–1078, 2010. URL http://www.sciencedirect.com/science/article/pii/S136403210900269X.

M. A. Rastegar, E. Guerci, and S. Cincotti. Agent-based model of the Italian wholesale electricity market. In *Energy Market, 2009. EEM 2009. 6th International Conference on the European*, pages 1–7, 2009. URL 10.1109/EEM.2009.5207128.

Lord Rayleigh. LIX. On convection currents in a horizontal layer of fluid, when the higher temperature is on the under side. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 32(192):529–546, 1916.

REF. Installed Renewable Energy Generators database, 2012. URL http://www.ref.org.uk/energy-data.

Klaus Rennings. Introduction: Global diffusion of environmental innovations. *Environmental Innovation and Societal Transitions*, 10(0):1–3, March 2014. ISSN 2210-4224. doi: 10.1016/j.eist.2013.12.005. URL http://www.sciencedirect.com/science/article/pii/S2210422413000956.

Craig W. Reynolds. Flocks, Herds and Schools: A Distributed Behavioral Model. In *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '87, pages 25–34, New York, NY, USA, 1987. ACM. ISBN 978-0-89791-227-3. doi: 10.1145/37401.37406. URL http://doi.acm.org/10.1145/37401.37406.

A. Rip and R. Kemp. Technological change. In S. Rayner and E.L. Malone, editors, *Human choice and climate change*, volume 2, pages 327–399. Battelle Prêss, 1998.

Scott A. Robinson, Matt Stringer, Varun Rai, and Abhishek Tondon. GIS-Integrated Agent-Based Model of Residential Solar PV Diffusion, 2013. URL http://www.usaee.org/usaee2013/submissions/OnlineProceedings/GIS_integrated_ABM_5302013.pdf.

Everett M. Rogers. Diffusion of innovations. *Diffusion of innovations.*, 1962.

Everett M. Rogers. *The Diffusion of Innovation (3rd Edition)*. The Free Press, New York, 1983.

Everett M. Rogers, Una E. Medina, Mario A. Rivera, and Cody J. Wiley. Complex Adaptive Systems and the Diffusion of Innovations. *Innovation Journal*, 10(3):2–26, December 2005. URL http://www.innovation.cc/volumes-issues/rogers-adaptivesystem7final.pdf.

A.J. Roscoe and G. Ault. Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response. *Renewable Power Generation, IET*, 4(4):369–382, 2010. ISSN 1752-1416.

Daniel Rosenbloom and James Meadowcroft. The journey towards decarbonization: Exploring socio-technical transitions in the electricity sector in the province of Ontario (1885–2013) and potential low-carbon pathways. *Energy Policy*, 65(0):670–679, February 2014. ISSN 0301-4215. doi: 10.1016/j.enpol.2013.09.039. URL http://www.sciencedirect.com/science/article/pii/S0301421513009634.

A. E. Roth and I. Erev. Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term*. *Games and economic behavior*, 8(1):164–212, 1995.

Mark Rylatt, Rupert Gammon, Peter Boait, Liz Varga, Peter Allen, Mark Savill, J. Richard Snape, Mark Lemon, Babak Ardestani, and Vijay Pakka. Cascade: an agent based framework for modeling the dynamics of smart electricity systems. *Emergence: Complexity & Organization*, 15(2), 2013.

R. Mark Rylatt, J. Richard Snape, Peter Allen, Babak M. Ardestani, Peter Boait, Ekkehard Boggasch, Denis Fan, Graham Fletcher, Rupert Gammon, Mark Lemon, Vijay Pakka, Christophe Rynikiewicz, Mark Savill, Stefan Smith, Mark Strathern, and Liz Varga. Exploring Smart Grid Possibilities: A Complex Systems Modelling Approach. *Smart Grid*, 1(1), 2015. ISSN 22991107. doi: 10.1515/sgrid-2015-0001. URL //www.degruyter.com/view/j/sgrid.2015.1.issue-1/sgrid-2015-0001/sgrid-2015-0001.xml.

T. Schelling. Dynamic Models of Segregation. *Journal of Mathematical Sociology*, 1(2):143–186, 1971.

M. Schilperoord, J. Rotmans, and N. Bergman. Modelling societal transitions with agent transformation. *Computational & Mathematical Organization Theory*, 14(4):283–301, 2008.

Johan Schot and Arie Rip. The past and future of constructive technology assessment. *Technological forecasting and social change*, 54(2):251–268, 1997.

Mary E. Schramm, Kevin J. Trainor, Murali Shanker, and Michael Y. Hu. An agent-based diffusion model with consumer and brand agents. *Decision Support Systems*, 50(1):234–242, 2010.

S. H. Schwartz. Normative explanations of helping behavior: A critique, proposal, and empirical test* 1. *Journal of Experimental Social Psychology*, 9(4):349–364, 1973.

Nina Schwarz and Andreas Ernst. Agent-based modeling of the diffusion of environmental innovations—an empirical approach. *Technological forecasting and social change*, 76(4): 497–511, 2009. doi: doi:10.1016/j.techfore.2008.03.024. URL Agent-based%0020modeling%0020of%0020the%0020diffusion%0020of%0020environmental%0020innovations%0020%0014%0020An%0020empirical%0020approach.

Ashley Seager. Public supports ambitious scheme for micro-scale renewable energy: poll. *The Guardian*, January 2010. ISSN 0261-3077. URL http://www.theguardian.com/environment/2010/jan/27/feed-in-tariffs-renewable-energy.

P. M. Senge. The fifth discipline: Mastering the five practices of the learning organization. *New York*, 1990.

F. Sensfuß and M. Genoese. Agent-based simulation of the German electricity markets-An analysis of the German spot market prices in the year 2001. In *Proceedings of the*, volume 9, pages 02.2006–17.02, 2006.

F. Sensfuß and M. Ragwitz. An agent-based simulation platform as support tool for the analysis of the interactions of renewable electricity generation with the electricity and CO2 market. In *New methods for energy market modelling*, page 63, Karlsruhe, Germany, 2008.

F. Sensfuß, M. Ragwitz, M. Genoese, and D. Möst. Agent-based simulation of electricity markets: a literature review. Working Paper S 5/2007, Fraunhofer institute for Systems and Innovation research, 2007.

F. Sensfuß, M. Genoese, and M. Ragwitz. Analysis of the impact of renewable electricity generation on CO2 emissions and power plant operation in Germany. In *Proceedings of the 10. Symposium Energieinnovation (EnInnov 08), TU Graz, Institut für Elektrizitätswirtschaft und Energieinnovation*, volume 13, page 15, 2008.

S. Shackley and K. Green. A conceptual framework for exploring transitions to decarbonised energy systems in the United Kingdom. *Energy*, 32(3):221–236, 2007.

Elizabeth Shove and Gordon Walker. CAUTION! Transitions ahead: politics, practice, and sustainable transition management. *Environment and Planning A*, 39(4):763–770, 2007.

Elizabeth Shove and Gordon Walker. What Is Energy For? Social Practice and Energy Demand. *Theory, Culture & Society*, 31(5):41–58, September 2014. doi: 10.1177/0263276414536746. URL http://tcs.sagepub.com/content/31/5/41.abstract.

H. A. Simon. A behavioral model of rational choice. *The quarterly journal of economics*, 69(1): 99–118, 1955.

R. B. Skeie, T. Berntsen, M. Aldrin, M. Holden, and G. Myhre. A lower and more constrained estimate of climate sensitivity using updated observations and detailed radiative forcing time series. *Earth Syst. Dynam.*, 5(1):139–175, March 2014. ISSN 2190-4987. doi: 10.5194/esd-5-139-2014. URL http://www.earth-syst-dynam.net/5/139/2014/.

Adrian Smith, Andy Stirling, and Frans Berkhout. The governance of sustainable socio-technical transitions. *Research policy*, 34(10):1491–1510, 2005.

J. Richard Snape. Smart grids, local adoption of distributed generation and the feed in tariff policy incentive. In *Energy efficiency first: The foundation of a low-carbon society - Proceeding of eceee 2013 Summer Study*, volume 1-163-13 of *Proceedings 2013, Rethink, renew, restart*, pages 93–99, Belambra Presqu'île de Giens, France, June 2013. ECEEE. ISBN 978-91-980482-3-0. URL http://proceedings.eceee.org/visabstrakt.php?event=3&doc=1-163-13.

J. Richard Snape, P. J. Boait, and R. M. Rylatt. Will domestic consumers take up the renewable heat incentive? An analysis of the barriers to heat pump adoption using agent-based modelling. *Energy Policy*, 85:32–38, 2015. doi: 10.1016/j.enpol.2015.05.008. URL www.sciencedirect.com/science/article/pii/S0301421515002013.

Solar Plaza. Spain'S Solar Sector Fights Unfair Self-Consumption Law | Solarplaza | The global solar energy (PV) platform. *Solar Plaza magazine*, June 2015. URL http://www.solarplaza.com/article/spains-solar-sector-fights-unfair-self-consumption.

Bertha Maya Sopha and Christian A. Klöckner. Psychological factors in the diffusion of sustainable technology: A study of Norwegian households' adoption of wood pellet heating. *Renewable and Sustainable Energy Reviews*, 15(6):2756–2765, August 2011. ISSN 1364-0321. doi:

10.1016/j.rser.2011.03.027. URL http://www.sciencedirect.com/science/article/pii/S1364032111001304.

Bertha Maya Sopha, Christian A. Klöckner, and Edgar G. Hertwich. Adopters and non-adopters of wood pellet heating in Norwegian households. *Biomass and Bioenergy*, 35(1): 652–662, January 2011. ISSN 0961-9534. doi: doi:\%0020DOI:\%002010.1016/j.biombioe.2010.10.019. URL http://www.sciencedirect.com/science/article/B6V22-51FFT5R-2/2/61a264b6a4553dfdd5a56e70dc6de6bd.

Bertha Maya Sopha, Christian A. Klöckner, and Edgar G. Hertwich. Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions*, 8(0):42–61, September 2013. ISSN 2210-4224. doi: 10.1016/j.eist.2013.06.001. URL http://www.sciencedirect.com/science/article/pii/S2210422413000427.

P. C. Stern. New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of social issues*, 56(3):407–424, 2000.

Fred Steward. Transformative innovation policy to meet the challenge of climate change: sociotechnical networks aligned with consumption and end-use as new transition arenas for a low-carbon society or green economy. *Technology Analysis & Strategic Management*, 24(4): 331–343, March 2012. ISSN 0953-7325. doi: 10.1080/09537325.2012.663959. URL http://dx.doi.org/10.1080/09537325.2012.663959.

Goran Strbac. Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426, December 2008. ISSN 0301-4215. doi: 10.1016/j.enpol.2008.09.030. URL http://www.sciencedirect.com/science/article/pii/S0301421508004606.

J. Sun and L. Tesfatsion. Dynamic testing of wholesale power market designs: An open-source agent-based framework. *Computational Economics*, 30(3):291–327, 2007a.

J. Sun and L. Tesfatsion. Open-source software for power industry research, teaching, and training: A DC-OPF illustration. In *IEEE Power Engineering Society General Meeting, 2007*, pages 1–6, 2007b.

Marcel Šúri, Thomas A. Huld, Ewan D. Dunlop, and Heinz A. Ossenbrink. Potential of solar electricity generation in the European Union member states and candidate countries. *Solar Energy*, 81(10):1295–1305, October 2007. ISSN 0038-092X. doi: 10.1016/j.solener.2006.12.007. URL http://www.sciencedirect.com/science/article/pii/S0038092X07000229.

John Thøgersen and Alice Grønhøj. Electricity saving in households–A social cognitive approach. *Energy Policy*, 38(12):7732–7743, December 2010. ISSN 0301-4215. doi: doi:\%0020DOI:\%002010.1016/j.enpol.2010.08.025. URL http://www.sciencedirect.com/science/article/B6V2W-512DT29-2/2/1fdf79394d51bd9880fd5e653388f01c.

Warren Thorngate and Bruce Edmonds. Measuring Simulation-Observation Fit: An Introduction to Ordinal Pattern Analysis. *Journal of Artificial Societies and Social Simulation*, 16(2):4, 2013. ISSN 1460-7425.

A. Toffler. *The third wave*. Bantam Books New York, 1981.

Martino Tran. Technology-behavioural modelling of energy innovation diffusion in the UK. *Applied Energy*, 95:1–11, July 2012a. ISSN 0306-2619. doi: 10.1016/j.apenergy.2012.01.018. URL http://www.sciencedirect.com/science/article/pii/S0306261912000244.

Martino Tran. Agent-behaviour and network influence on energy innovation diffusion. *Communications in Nonlinear Science and Numerical Simulation*, 17(9):3682–3695, September 2012b. ISSN 1007-5704. doi: 10.1016/j.cnsns.2012.01.016. URL http://www.sciencedirect.com/science/article/pii/S100757041200038X.

Martino Tran, David Banister, Justin D.K. Bishop, and Malcolm D. McCulloch. Simulating early adoption of alternative fuel vehicles for sustainability. *Technological Forecasting and Social Change*, 2012. ISSN 0040-1625. doi: 10.1016/j.techfore.2012.09.009. URL http://www.sciencedirect.com/science/article/pii/S0040162512002211.

H. C. Triandis. *Interpersonal behavior*. Brooks/Cole Pub. Co., Monterey, 1977. ISBN 0-8185-0188-X.

Bruno Turnheim, Frans Berkhout, Frank Geels, Andries Hof, Andy McMeekin, Björn Nykvist, and Detlef van Vuuren. Evaluating sustainability transitions pathways: Bridging analytical approaches to address governance challenges. *Global Environmental Change*, 35:239–253, November 2015. ISSN 0959-3780. doi: 10.1016/j.gloenvcha.2015.08.010. URL http://www.sciencedirect.com/science/article/pii/S0959378015300315.

UK Data Service. GeoConvert, UK Data Service, March 2013. URL http://geoconvert.mimas.ac.uk/index.htm. This is a description.

UK Government. The Carbon Plan. Government report, UK Government, London, November 2011. URL https://www.gov.uk/government/publications/the-carbon-plan-reducing-greenhouse-gas-emissions--2.

UK Government. Energy Bill, June 2013. URL http://www.publications.parliament.uk/pa/bills/lbill/2013-2014/0030/lbill_2013-20140030_en_1.htm. Make provision for the setting of a decarbonisation target range and duties in relation to it; for or in connection with reforming the electricity market for purposes of encouraging low carbon electricity generation or ensuring security of supply; for the establishment and functions of the Office for Nuclear Regulation; about the government pipe-line and storage system and rights exercisable in relation to it; about the designation of a strategy and policy statement; about domestic supplies of gas and electricity; for extending categories of activities for which energy licences are required; for the making of orders requiring regulated persons to provide redress to consumers of gas or electricity; about offshore transmission of electricity during a commissioning period; for imposing fees in connection with certain costs incurred by the Secretary of State; and for connected purposes.

UK Government. Energy Bill, 2015. URL http://www.publications.parliament.uk/pa/bills/lbill/2013-2014/0030/lbill_2013-20140030_en_1.htm. Make provision for the setting of a decarbonisation target range and duties in relation to it; for or in connection with reforming the electricity market for purposes of encouraging low carbon electricity generation or ensuring security of supply; for the establishment and functions of the Office for Nuclear Regulation; about the government pipe-line and storage system and rights exercisable in relation to it; about the designation of a strategy and policy statement; about domestic supplies of gas and electricity; for extending categories of activities for which energy licences are required; for the making of orders requiring regulated persons to provide redress to consumers of gas or electricity; about offshore transmission of electricity during a commissioning period;

for imposing fees in connection with certain costs incurred by the Secretary of State; and for connected purposes.

UK Parliament. Climate Change Act 2008, 2008a. URL http://www.legislation.gov.uk/ukpga/2008/27/contents.

UK Parliament. Energy Act 2008, November 2008b. URL http://www.legislation.gov.uk/ukpga/2008/32/contents.

UK Parliament. Energy Act 2010, April 2010. URL http://www.legislation.gov.uk/ukpga/2010/27/contents. An Act to make provision relating to the demonstration, assessment and use of carbon capture and storage technology; to make provision about reports on decarbonisation of electricity generation and development and use of carbon capture and storage technology; to make provision for requiring benefits to be provided by holders of gas or electricity supply licences; to make provision about functions of the Gas and Electricity Markets Authority; to make provision about general duties of the Secretary of State in relation to gas and electricity markets; to make provision about electricity generation licences; to make provision about persons authorised to supply gas or electricity; and for connected purposes.

UK Parliament. Energy Act 2011, October 2011. URL http://www.legislation.gov.uk/ukpga/2011/16/contents/enacted/data.htm.

UK Parliament. The Feed-in Tariffs Order 2012, 6th November 2012. URL http://www.legislation.gov.uk/uksi/2012/2782/introduction/made.

UN. Kyoto Protocol to the United Nations Framework Convention on Climate Change, 1998. URL http://unfccc.int/kyoto_protocol/items/2830.php.

VDS Technologies. GeoMerge, 2007. URL http://www.vdstech.com/geomerge.aspx.

D. J Veit, A. Weidlich, J. Yao, and S. S Oren. Simulating the dynamics in two-settlement electricity markets via an agent-based approach. *International Journal of Management Science and Engineering Management*, 1(2):83–97, 2006.

G. P. J. Verbong and F. W. Geels. The ongoing energy transition: Lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960-2004). *Energy Policy*, 35(2):1025–1037, 2007.

G. P. J. Verbong and F. W. Geels. Exploring sustainability transitions in the electricity sector with socio-technical pathways. *Technological Forecasting and Social Change*, 77(8):1214–1221, October 2010. ISSN 0040-1625. doi: doi:\%0020DOI:\%002010.1016/j.techfore.2010.04.008. URL http://www.sciencedirect.com/science/article/pii/S0040162510000752.

Geert P.J. Verbong, Sjouke Beemsterboer, and Frans Sengers. Smart grids or smart users? Involving users in developing a low carbon electricity economy. *Special Section: Transition Pathways to a Low Carbon Economy*, 52(0):117–125, January 2013. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.05.003. URL http://www.sciencedirect.com/science/article/pii/S0301421512004004.

Thomas Veselka, Gale Boyd, Guenter Conzelmann, Vladimir Koritarov, Charles Macal, Michael North, Benjamin Schoepfle, and Prakash Thimmapuram. Simulating the behavior of electricity markets with an agent-based methodology: the Electric Market Complex Adaptive Systems (EMCAS) model. *Vancouver, Canada*, 2002.

M. Mitchell Waldrop. *Complexity: The emerging science and the edge of order and chaos*. Simon & Schuster, 1992. ISBN 0-671-76789-5.

R. Wall and T. Crosbie. Potential for reducing electricity demand for lighting in households: An exploratory socio-technical study. *Energy Policy*, 37(3):1021–1031, 2009.

Rainer Walz and Jonathan Köhler. Using lead market factors to assess the potential for a sustainability transition. *Global Diffusion of Environmental Innovations*, 10(0):20–41, March 2014. ISSN 2210-4224. doi: 10.1016/j.eist.2013.12.004. URL http://www.sciencedirect.com/science/article/pii/S2210422413000944.

Peter Warren. A review of demand-side management policy in the UK. *Renewable and Sustainable Energy Reviews*, 29:941–951, January 2014. ISSN 1364-0321. doi: 10.1016/j.rser.2013.09.009. URL http://www.sciencedirect.com/science/article/pii/S1364032113006680.

C. J.C.H Watkins and P. Dayan. Q-learning. *Machine learning*, 8(3):279–292, 1992.

A. Weidlich and D. Veit. A critical survey of agent-based wholesale electricity market models. *Energy Economics*, 30(4):1728–1759, 2008.

E. Wenger. Communities of Practice and Social Learning Systems. *Organization*, 7(2):225–246, 2000. URL http://org.sagepub.com/content/7/2/225.abstract.

Which? Energy. Feed-in tariff cuts - Feed-in tariffs explained, July 2014. URL http://www.which.co.uk/energy/creating-an-energy-saving-home/guides/feed-in-tariffs-explained/feed-in-tariff-cuts/.

H. Wilhite, E. Shove, L. Lutzenhiser, and W. Kempton. The legacy of twenty years of energy demand management: We know more about individual behaviour but next to nothing about demand. *Society, behaviour, and climate change mitigation*, pages 109–126, 2003.

Harold Wilhite. New thinking on the agentive relationship between end-use technologies and energy-using practices. *Energy Efficiency*, 1:121–130, 2008. ISSN 1570-646X. URL http://dx.doi.org/10.1007/s12053-008-9006-x. 10.1007/s12053-008-9006-x.

Nick Winser. Hunter Memorial Lecture 2010: Britain's Energy Mix and the National Grid, 2010-2030, December 2010. URL http://tv.theiet.org/technology/power/10204.cfm. http://scpro.streamuk.com/uk/player/Default.aspx?wid=10204&ptid=32&t=0 Actual streaming video.

Stephen Wolfram. *A new kind of science*, volume 5. Wolfram media Champaign, 2002.

Michael Wooldridge. *An introduction to multiagent systems*. Wiley. com, 2008. ISBN 0-470-35347-3.

Dimitrios Xenias, Colin Axon, Nazmiye Balta-Ozkan, Liana Cipcigan, Peter Connor, Rosemary Davidson, Alexa Spence, Gary Taylor, and Lorraine Whitmarsh. Scenarios for the Development of Smart Grids in the UK: Literature Review. Working Paper UKERC/WP/ES/2014/001, UKERC, London, January 2014.

R. Zegers. *Exploring the Potential of SocioTechnical Systems*. Msc: Technology and policy, Eindhoven University of Technology, Eindhoven, 2009.

A. M Zhabotinsky. Periodic processes of malonic acid oxidation in a liquidphase. *Biofizika*, 9: 306, 1964.

T. Zhang and W. J. Nuttall. An agent based simulation of smart metering technology adoption. EPRG working paper 0727, University of Cambridge, Cambridge, 2007.

T. Zhang and W. J. Nuttall. Evaluating government's policies on promoting smart metering in retail electricity markets via agent based simulation. EPRG working paper 0822, Judge Institute, Cambridge University, Cambridge, England, 2008.

Tao Zhang. *Agent based simulation of energy trends : a study of smart metering technology diffusion in the electricity market via a complexity science approach*. Ph.d., University of Cambridge, Cambridge, England, 2011. URL http://ethos.bl.uk/OrderDetails.do?uin=uk.bl.ethos.609344.

Tao Zhang and William J. Nuttall. Evaluating Government's Policies on Promoting Smart Metering Diffusion in Retail Electricity Markets via Agent-Based Simulation*. *Journal of Product Innovation Management*, 28(2):169–186, 2011. ISSN 1540-5885. URL http://dx.doi.org/10.1111/j.1540-5885.2011.00790.x.

Tao Zhang, Peer-Olaf Siebers, and Uwe Aickelin. Modelling the Effects of User Learning on Forced Innovation Diffusion. *arXiv:1307.1694 [cs]*, July 2013. URL http://arxiv.org/abs/1307.1694.

Ting Zhang, Sonja Gensler, and Rosanna Garcia. A Study of the Diffusion of Alternative Fuel Vehicles: An Agent-Based Modeling Approach. *Journal of Product Innovation Management*, 28 (2):152–168, March 2011. ISSN 07376782. URL http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib&db=bth&AN=58058273&site=ehost-live.

Z. Zhou, W. K. V. Chan, and J. H. Chow. Agent-based simulation of electricity markets: a survey of tools. *Artificial Intelligence Review*, 28(4):305–342, 2007.

Appendix A

Published works including input from work conducted within this PhD

A.1 Journal articles

Snape, J.R., Boait, P.J., Rylatt, R.M., 2015. Will domestic consumers take up the renewable heat incentive? An analysis of the barriers to heat pump adoption using agent-based modelling. Energy Policy 85, 32–38.

Rylatt, R.M., Snape, J.R., Allen, P., Ardestani, B.M., Boait, P., Boggasch, E., Fan, D., Fletcher, G., Gammon, R., Lemon, M., 2015. Exploring Smart Grid Possibilities: A Complex Systems Modelling Approach. Smart Grid 1.

Rylatt, M., Gammon, R., Boait, P., Varga, L., Allen, P., Savill, M., Snape, R., Lemon, M., Ardestani, B., Pakka, V., 2013. Cascade: an agent based framework for modeling the dynamics of smart electricity systems. Emergence: Complexity & Organization 15.

Boait, P.J., Ardestani, B.M., Rylatt R. Mark, and Snape, J. Richard. 2013. 'Managing Complexity in the Smart Grid through a New Approach to Demand Response'. Emergence: Complexity and Organization 15 (SPL. 2): 23–37.

Boait, P., Ardestani, B.M., Snape, J.R., 2013b. Accommodating renewable generation through an aggregator-focused method for inducing demand side response from electricity consumers. Renewable Power Generation, IET 7, 689–699.

A.2 Peer reviewed conference papers

Snape, J.R., 2013. 'Smart Grids, Local Adoption of Distributed Generation and the Feed in Tariff Policy Incentive'. In Energy Efficiency First: The Foundation of a Low-Carbon Society - Proceeding of Eceee 2013 Summer Study, 1-163-13:93–99. Proceedings 2013, Rethink, Renew, Restart. Belambra Presqu'île de Giens, France: ECEEE. http://proceedings.eceee.org/visabstrakt.php?event=3&doc=1-163-13

Snape, J.R., Boait, P., 2013. Enhancing efficiency through smart control: paths and policies for deployment. In Energy Efficiency First: The Foundation of a Low-Carbon Society - Proceeding of Eceee 2013 Summer Study, 5A-162-13:1173-1182. Proceedings 2013, Rethink, Renew, Restart. Belambra Presqu'île de Giens, France: ECEEE. http://proceedings.eceee.org/visabstrakt.php?event=3&doc=5A-162-13

Snape, J.R., Irvine, K., Rynikiewicz, C., 2011. Understanding energy behaviours and transitions through the lens of a smart grid Agent Based Model, in: Energy Efficiency First: The Foundation of a Low-Carbon Society - Proceeding of Eceee 2011 Summer Study. Presented at the eceee 2011 summer study, ECEEE, Belambra Presqu'île de Giens, France, pp. 1919–1930.

Boait, P., Ardestani, B.M., Snape, J.R., 2013a. Levelling of heating and vehicle demand in distribution networks using randomised device control, in: 22nd International Conference on Electricity Distribution (CIRED). Presented at the International Conference on Electricity Distribution (CIRED), Stockholm.

A.3 Industry Journal article

Snape, J.R., Rynikiewicz, C., 2012. Peer effect and social learning in micro-generation adoption and urban smarter grids development? Network Industries Quarterly 14, 24–27.

A.4 Book sections

Rynikiewicz, C., Snape, J.R., 2012. Islands of hope: seeds for wider energy transitions?, in: Topsø Larsen, K. (Ed.), FROM ONE ISLAND TO ANOTHER: A Celebration of Island Connections. Centre for Regional Tourism (CRT), Bornholm, Denmark, pp. 179–190.

A.5 Conference paper

Rynikiewicz, C., Snape, J.R., 2010. Investigating the peculiarities of sustainable energy policies in islands communities for smart grid development: insights from complexity science and agent based models, in: Islands of the World XI - Celebrating Island Connectivities, International Small Islands Study Association (ISISA). Presented at the Islands of the World XI - Celebrating Island Connectivities, Bornholm, Denmark

Appendix B

SQL used in data analysis

B.1 Get statistics for FiT uptake

```
SELECT technology_type,count(fit_id)
FROM fit_installations_30_Jun_2013
GROUP BY technology_type
```

B.2 Get FiT database available fields

```
SHOW columns FROM fit_installations
```

B.3 Get duplicated FiT IDs

```
SELECT fit_id, f_count
  FROM (SELECT fit_id,count(fit_id) as f_count
             from fit_installations_30_Jun_2013
             group by fit_id) as mFit
  WHERE f_count > 1
```

B.4 Get rows affected by duplicate FiT ID

```
SELECT fit_installations_30_Jun_2013.*
   FROM fit_installations_30_Jun_2013, (SELECT fit_id, f_count
       FROM SELECT fit_id,count(fit_id) as f_count from
       fit_installations_30_Jun_2013 group by fit_id) as mFit where
       f_count > 1) as multi_fit_id
       WHERE fit_installations_30_Jun_2013.fit_id = multi_fit_id.fit_id
```

B.5 Find installs with declared capacity less than installed capacity

```
SELECT * FROM fit_installations_30_Jun_2013
WHERE (fit_installations_30_Jun_2013.installed_capacity_kw
          - fit_installations_30_Jun_2013.declared_net_capacity_kw) > 0
      and technology_type = "Photovoltaic"
```

B.6 Find installations that disappear between data releases

```sql
SELECT * FROM (select fit_installations.*,
fit_installations_30_Jun_2013.fit_id as newer_fitid
FROM fit_installations
LEFT OUTER JOIN
fit_installations_30_Jun_2013 on fit_installations.fit_id
    = fit_installations_30_Jun_2013.fit_id and
fit_installations.commissioned_date
    = fit_installations_30_Jun_2013.commissioned_date) as q1
WHERE q1.newer_fitid is null
```

B.7 Find average PV installed capacity by sector

```sql
SELECT AVG(fit_installations_30_Jun_2013.declared_net_capacity_kw),
fit_installations_30_Jun_2013.installation_type
FROM fit_installations_30_Jun_2013
WHERE technology_type="Photovoltaic" group by installation_type
```

B.8 PV installed capacity by LLSOA

```sql
SELECT count(fit_id),
  sum(fit_installations_30_Jun_2013.declared_net_capacity_kw), llsoa_code
  FROM fit_installations_30_Jun_2013
  WHERE fit_installations_30_Jun_2013.commissioned_date < date("2010-04-01")
  GROUP BY fit_installations_30_Jun_2013.llsoa_code
```

[Todo: Check all SQL from data chapter endnotes added here]

Appendix C

Code used in data analysis

C.1 Python code for OPA implementation

```
'''
Created on 15 May 2013

@author: jsnape

takes a file with first line as reference (or simulation) output

all other lines observations.

Produces stats of misses, hits, ties and other metrics as per
Thorngate and Edmonds 2013 for each line
'''
import random

def getPairs(myList):
    listLen = len(myList)
    retList = []
    for i in xrange(len(myList),0,-1):
        n=myList[i-1]
        for j in xrange(i,0,-1):
            if myList[j-1] < n:
                retList += [i-1,j-1]
    return retList

def OPA_analyse(predictions,observations):
    numPairs = len(predictions)/2
    hits = 0
    ties = 0
    misses = 0
    NAs = 0
    for test in xrange(numPairs):
        a=predictions[test+test]
        b=predictions[test+test+1]
        if observations[a] in {"NA",""} or observations[b] in {"NA",""}:
            NAs+=1
        elif observations[a] > observations[b]:
            hits+=1
        elif observations[a] == observations[b]:
            ties+=1
        elif observations[a] < observations[b]:
            misses+=1

    return (hits,misses,ties,NAs)

def rowToList(l):
    l=l.strip('\n')
```

```
    l=l.split(",")
    for (i,n) in enumerate(l[1:]):
        if n!="NA":
            l[i+1]=int(n)
    return l

def OPA_display(statSet):
    if statSet[0]+statSet[1] == 0:
        PM = None
        IOF = None
    else:
        PM = statSet[0]*1.0/(statSet[0]+statSet[1])
        IOF = PM+PM-1

    print "Matches\t:",statSet[0]
    print "MisMatches\t:",statSet[1]
    print "Ties\t:",statSet[2],";␣NAs\t\t:",statSet[3]
    print "PM␣(Probability␣of␣a␣match)␣=",PM
    print "IOF␣(Index␣of␣observed␣fit)␣=",IOF

    return IOF

def bootstrapResample(myList,n=None):
    l=len(myList)
    if not n:
        n=l
    res=[]
    for i in xrange(n):
        a=myList[random.randint(0,l-1)]
        res.append(a)
    return res

nSample = 200
simLabel=""
#f=open("Dataset.csv",'r+')
#f=open("Trends_per_postcode_for_OPA.csv",'r+')
#f=open("trends_post_apr_2010_for_OPA.csv",'r+')
f=open("trends_post_apr_2010_for_OPA.csv",'r+')
fnotSame = open ("PCode_OPA_overP.csv",'w')
fSimilar = open("PCode_OPA_underP.csv",'w')

largePVals=[]
firstLine=True
for l in f:
    l=rowToList(l)
    label=l[0]
    l=l[1:]
    if firstLine:
        preds = getPairs(l)
        simLabel=label
        #print preds
        firstLine = False
    else:
        stats=OPA_analyse(preds,l)
        print "OPA␣stats␣for",label,"vs.",simLabel
        IOF=OPA_display(stats)
        exceeds=0
        r=l
        if nSample > 0:
            for i in xrange(nSample):
                r = random.sample(l,len(l))#bootstrapResample(l)
                nStat = OPA_analyse(preds,r)
                if nStat[0] >= stats[0]:
                    exceeds+=1
```

```
            p=exceeds*1.0 / nSample
            print "P(Number␣of␣matches␣>=␣obtained␣matches)␣=",p
            if p>0.05:
                fnotSame.write(label+":"+str(p)+";IOF="+str(IOF)+"\n")
            else:
                fSimilar.write(label+":"+str(p)+";IOF="+str(IOF)+"\n")
```

C.2 Python code for calculation of mean sd and skew of simulation output distributions

```
import pandas as pd
from os import listdir
import re

#Note that this uses the bias_factor, but is probably irrelevant as very near zero
def fisher_pearson(data, ybar, sample_sd):
    N = len(data)
    #for skewness - the sd should be calculated using n rather than n-1 sort
    #so turn the sample sd into a population one
    sd = ((N-1) * sample_sd )/ N
    sum_term = 0
    for y in data:
        sum_term+=(y-ybar)**3
    print sum_term
    sum_term = sum_term / N

    bias_multiplier = ((N*1.0)*(N-1))**0.5 / (N-1)
    print bias_multiplier
    print "returning",bias_multiplier * sum_term / (sd**3)
    return bias_multiplier * sum_term / (sd**3)

def standard_dev(data, ybar):
    sum_term = 0
    for y in data:
       sum_term += (y - ybar)**2
    return (sum_term / (len(data)-1))**0.5

files = [f for f in listdir('.') if 'csv' in f]

all_results = pd.DataFrame(columns=['mu','sigma','mean','sd','skew'])

print all_results
i=0

for f in files:
    m = re.match(r"compiled_mean_(.+)var_(.+).csv", f)
    mu, sigma = m.group(1),m.group(2)
    mu, sigma = float(mu), float(sigma)
    lastrow = None

    with open(f) as csvfile:
        for row in csvfile:
            lastrow = row
        lastrow = lastrow.strip().split(',')[:-1] #Hack to remove empty cell at end
        lastrow = map(float,lastrow)

    mean = sum(lastrow) / len(lastrow)
    sd = standard_dev(lastrow, mean)
    skew = fisher_pearson(lastrow, mean, sd)

    all_results.loc[i] = [mu,sigma,mean,sd,skew]
    i+=1

print all_results
```